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2020

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American Society of Farm Managers & Rural Appraisers

Letter from the Editorial Committee Chair

DR. GREGORY IBENDAHL

Associate Professor at Kansas State University & Editorial Committee Chair

Dear ASFMRA Members and Friends of Agriculture:

The ASFMRA Editorial Committee is proud to present the Society's 2020 Journal. This year, 19 papers were accepted for publication in the Journal. This collection of papers provided our Committee with a wide assortment of topics to review and evaluate for your reading pleasure.

You will find topics on most of the appraisal, management, and agricultural consulting issues that we frequently see and/or experience in our respective professions. These papers include research and case studies illustrating new, reformed, and/or revised ideas and techniques.

Examples of the many topics included in the *2020 Journal of ASFMRA* are:

- Land renting
- Profitability of different enterprises
- Cost control
- Decision-making
- Risk management

The 2020 Journal contains the most up-to-date collection of rural appraisal, agricultural consulting, and farm management topics available in the world. In the following pages you will find cutting-edge manuscripts documenting research, field studies, practices, and methodologies proposed by the leading academic, appraisal, consulting, and management leaders of agriculture. This edition of the Journal continues to provide our membership and the agri-business community with topics on newly evolved issues and concepts for your review and consideration.

The Editorial Committee worked with the authors to ensure that each article was informative, clear, and precise in the presentation of data and conclusions, as well as consistent with ASFMRA goals. We particularly worked to find articles that were more applied and less theoretical.

The Editorial Committee continues its challenge to all readers to join our highly acclaimed group of published authors. Share some of your experiences and wisdom! Most of us have encountered at least one unusual problem or situation that required original and innovative thinking to develop workable solutions. If it was new for you, chances are it will be interesting and usable by others.

The Editorial Committee thanks you for your continued interest in the ASFMRA, agriculture, and the entire agricultural community.

Dr. Gregory Ibendahl
Associate Professor at Kansas State University and Editorial Committee Chair

Thank You to the 2019–20 Editorial Committee

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A Brief History of Farm Management

By Terry W. Griffin and Sara Gammon

Terry W. Griffin is an Associate Professor in the Department of Agricultural Economics at Kansas State University. Sara Gammon is an Undergraduate Student studying Agricultural Economics at Kansas State University.

Acknowledgment

Appreciation is expressed to Mary Huninghake for meticulous data collection and tedious database entry. We appreciate ASFMRA for maintaining open access to its journal. We appreciate the opensource community, especially the R Core Team and authors of contributed packages to R. To further the concept of open data and opensource, the data and R script used for this analysis are available on GitHub at https://github.com/spaceplowboy/GoldQuill. Running the script will produce the same graphs included in this article. It is our hope that others will learn more about writing code and build upon the analyses presented here. The lead author (i.e., principal investigator) takes full responsibility for any errors in the database, R script, and narrative.

Abstract

The Journal of ASFMRA *has a long-standing tradition of sharing farm management ideas and publishing the results of academic studies. A keyword analysis of titles from 330 published articles was conducted, along with an evaluation of the respective authors and their institutions. Comparisons between articles and the Gold Quill winners are discussed. Results of this analysis are of interest to authors considering submitting manuscripts to the* Journal of ASFMRA *and anyone interested in farm management and rural appraisal.*

INTRODUCTION

The *Journal of the American Society of Farm Managers and Rural Appraisers* (ASFMRA) (hereafter referred to as "the Journal") has been one of very few outlets of applied farm management. The Journal has provided a means for authors, largely academic researchers, to publish their studies under a peer review system. Consequently, the membership of ASFMRA has been provided with a steady flow of innovative ideas to consider in their farm management and rural appraisal practices. This mutually beneficial relationship has existed for the better part of a century.

The principal investigator decided to evaluate articles published in the Journal to test whether any farm management trends could be detected over time and whether articles deemed to be the most outstanding differed from those not selected for the honor. The Gold Quill Award is presented to authors of the most outstanding article in the Journal each year. Articles published in the Journal were evaluated by applying frequency and textual analysis of words appearing in article titles and the institutions of authors. Previous research has conducted textual analysis on titles of published articles, most notably Stephen's evaluation of *Human Communication Research* (1999). Information including author, institutions, title words, title length, farm management topic, and whether an article received the Gold Quill Award were analyzed. Differences between Gold Quill winners and other articles were also evaluated.

DATA AND METHODS

Data was collected from the publicly available archives of the Journal. Articles published from 2000–2019 were retrieved from ASFMRA and associated websites. Articles selected as Gold Quill Award recipients were identified from the past award winners (ASFMRA, 2018).

Articles published in the Journal were manually coded into a database. Transcriptionists collected pertinent data from each article and manually entered the information into the master database. Data transcription was accomplished via copy-and-paste procedures from electronic files or by manually typing pertinent information. Coded information included year of publication, last name of each author, geographic location of lead author, institution of each author, and title of article. Locations were coded by state if in the U.S. or by country otherwise. After pertinent information was entered, articles receiving the Gold Quill Award were signified by a binary variable (i.e., 1 if winner and 0 otherwise).

The principal investigator assigned articles to one of 11 general farm management categories: crops, finance, human, farmland, livestock, machinery, marketing, planning, policy, risk, and technology. Farm management categories were developed based on topics presented as chapters in the seminal farm management textbook by Kay, Edwards, and Duffy (2020). The “crops” category represents plant-based production, including field crops, specialty crops, horticultural crops, and forages. The “livestock” category includes any animal production such as bison, deer, dairy, cattle, swine, goats, sheep, catfish, and poultry.

Data cleaning procedures were applied to title words. Plural forms of words were converted to singular (Table 1), such as “prices” to “price,” “farmers” to “farmer,” etc. Similar words were converted to core representation; for example, “manage,” “manager,” and “managing” were replaced with “management.” Similar processes were applied for “growers” to “farmers,” “land” to “farmland,” and “crop” to “crops.” In this way, the word “farm” collectively represents “farm,” “farms,” and “farming” (Table 1). The word “farmer” represents “farmers,” “producers,” and “growers.”

Once the master database was replete with information from all publicly available articles, the data was analyzed using textual analysis and data mining procedures (Kosnik, 2015) with R statistical environment (R Core Team, 2019). Specifically contributed packages utilized included **tm** (Feinerer and Hornik, 2018; Feinerer, Hornik, and Meyer, 2008) and **wordcloud** (Fellows, 2018). The data and R script are publicly available on the principal investigator’s GitHub site for rural property professionals and other researchers to perform their own evaluations.

ANALYSIS AND RESULTS

The Journal has published 330 articles since 2000, nearly 17 articles per year with a maximum of 22 in 2010 and a minimum of 11 in 2017 (Figure 1). During this time period, most articles had fewer than four authors (Figure 2). The total number of authors contributing to articles each year varied from 26 in 2008 to 73 in 2009 and 2010 (Figure 3). Several authors have contributed to the Journal more than once. The number of co-authors was also assessed. Three authors were the most common, followed by two authors (Figure 2). Articles with single authors were third most common. The highest number of authors on a single article was 10.

In both academic publishing and industry, the first name on a journal article or wall of a building differentiates that individual. Names distinguish individuals and businesses and can set the tone for an article. The lead author of articles published in the Journal was evaluated (Figure 4). Most academic lead authors were associated with Kansas State University, followed by Purdue University (Figure 4). The second-largest group of authors was assigned to the catch-all for remaining non-academic institutions and referred to as “private sector.” The private sector group included independent rural appraisers, private research organizations, and commodity promotion associations. The University of Wyoming and the University of Illinois at Urbana-Champaign were tied for fourth-most articles. Authors from 31 academic institutions plus private sector firms and United States Department of Agriculture (USDA) agencies (e.g., ERS, NASS, and FSA) contributed lead authors to at least two articles. Considering all authors, not only lead authors, nearly 115 authors were associated with Kansas State University while Purdue University and the University of Wyoming each contributed nearly 55 and 75 authors, respectively (Figure 5). Nearly 85 authors were from the private sector not associated with any university or the USDA.

The number of words in titles was also evaluated. Current manuscript submission guidelines state that titles should be no longer than 10 words. The most common title length was nine words (Figure 6), followed by eight and 10. The longest title had 27 words, followed by 21 words. The shortest title had two words.

Most articles addressed the farm management topic of crops, followed by livestock and farmland. Planning and machinery were the least addressed farm management topics over the past 20 years. Fewer articles in the past decade have been focused on farmland relative to the 2000–2009 time period. The number of articles on crops remained nearly constant across decades but livestock articles fell by one-third. The number of machinery articles went from one during the 2000s to six in the 2010s. The proportion of articles addressing the 11 farm management topics each year are graphically represented in Figure 7.

Gold Quill Comparison to All Articles

Each year, the Journal bestows authors of the outstanding article with the Gold Quill Award. Given that outstanding articles were selected from the pool of all articles each year, Gold Quill recipients may have detectable differences. The metrics evaluated included number of authors, institution of authors, number of words in title, title words, and general farm management category addressed by the article. Since 2000, 16 lead authors have received the Gold Quill Award, with two lead authors receiving the award twice. One author from the University of Illinois at Urbana-Champaign penned three articles that were awarded the Gold Quill.

Four Gold Quill recipients were penned by a sole author (Figure 2). The highest number of co-authors of a Gold Quill winner was eight. No winners had six or seven co-authors. The most common number of co-authors for Gold Quill recipients was one, followed by two, then three, then four, then five (Figure 2).

Figure 5 indicates how many authors received the Gold Quill Award. Most notable include Kansas State University, the University of Kentucky, the University of Illinois at Urbana-Champaign, and the University of Idaho. The quantity of articles published in the Journal was not correlated with the number of Gold Quill Awards received. The University of Wyoming had the second-highest number of authors over the past 20 years but never received the Gold Quill Award. Other notable institutions publishing articles without an award include the University of Arkansas, Louisiana State University, and the USDA (although it should be noted that authors who published at these institutions won the award while at other institutions). Also notable, the University of Idaho won the award half as many times as its published articles. Additionally, several authors have contributed numerous articles without ever receiving the award.

Over the past 20 issues of the Journal, authors associated with the University of Illinois have been recipients of the most Gold Quill Awards, at nine (Figure 8). Faculty from Kansas State have received seven Gold Quill Awards. Kentucky authors received five awards. Seven institutions were associated with receiving the Gold Quill Award once. Five institutions received two awards. Private sector authors received three Gold Quill Awards.

The shortest title to win the Gold Quill since 2000 had two words, the shortest title for any article over the past 20 years (Figure 6). The longest title to receive the Gold Quill was 19 words; seemingly an outlier relative to the next longest title with 16 words. It was noted that two articles with 19-word titles received the Gold Quill. The most common title length of Gold Quill winners was tied at seven, eight, and 10 words.

Words from titles of articles were subjected to frequency analyses. The most common word across all article titles was "farm" (Figure 9). The most commonly used title words are graphically represented as a word cloud (Figure 10, part A for articles not receiving the Gold Quill and Figure 10, part B for Gold Quill recipients). Gold Quill recipients used "land," "value," "risk," and "lease" more often than authors not receiving the award. Commonly used title words that were not in titles of Gold Quill articles included "economic," "production," "crops," "farmer," "cost," and "price."

The number of times a word appeared in the title of a Gold Quill winner was compared to the total number of times that word appeared in titles of all articles (Figure 11). Data was sorted such that the word must appear in at least two Gold Quill articles to be considered. The words "flexible" and "environmental" were associated with Gold Quill winners two-thirds of the times they appeared in a title. The words "lease," "assessing," and "cash" appeared in Gold Quill titles more than a third of the number of times used in all articles. More commonly used words such as "farm," "impact," "management," "land," and "agriculture" had relatively low ratios near 0.1. The previously mentioned word "risk" was associated with Gold Quill winners almost 20% of the time it appeared in any published article.

The majority of farm management topics associated with articles winning the Gold Quill Award addressed farmland, with nine articles. The farm management topic "farmland" also had the highest ratio of Gold Quill to all articles (Table 2). The next most common farm management topic was a five-way tie between "finance," "human," "policy," "risk," and "technology." One Gold Quill article addressed "crops," which was the most common farm management topic across all articles. Four farm management topics—"livestock," "machinery," "marketing," and "planning"—have yet to be associated with a Gold Quill article.

SUMMARY

Articles published in the *Journal of ASFMRA* were evaluated for title words and authors' institutions. Trends were detected for specific universities contributing the majority of farm management literature. Some institutions and authors were much more successful in obtaining the Gold Quill Award than others. It was also discerned that the Gold Quill Award has not been proportionately given to authors at institutions that published the most articles. No algorithm exists to suggest that using or avoiding specific words in titles will ensure winning the Gold Quill Award; however, trends for future authors should be noted. It is unlikely that any permutations of "farm value analysis agriculture flexible farmland environmental risk market returns" will ensure receiving the award, even though the words "environmental," "flexible," and "risk" were associated with Gold Quill articles more than other words, given the frequency with which they appeared. Finally, Gold Quill recipients tended to adhere to the Journal's 10-word title requirement, an indication that value exists in following directions.

Proportions of basic farm management topics were imbalanced relative to the number of articles published in the Journal, although it is not clear if these topics need to be reevaluated or if authors should publish on these topics more. If the 11 topics are all truly core areas of farm management, it logically follows that all 11 would be somewhat uniformly represented as articles in the Journal, especially over long time periods. "Planning" and "machinery" rarely were represented over the past 20 years. Furthermore, the Gold Quill Award seemed to favor topics of farmland, although this may be an artifact of quality of individual researchers' interests. Future authors may consider additional work in areas of "planning," "machinery," and "technology."

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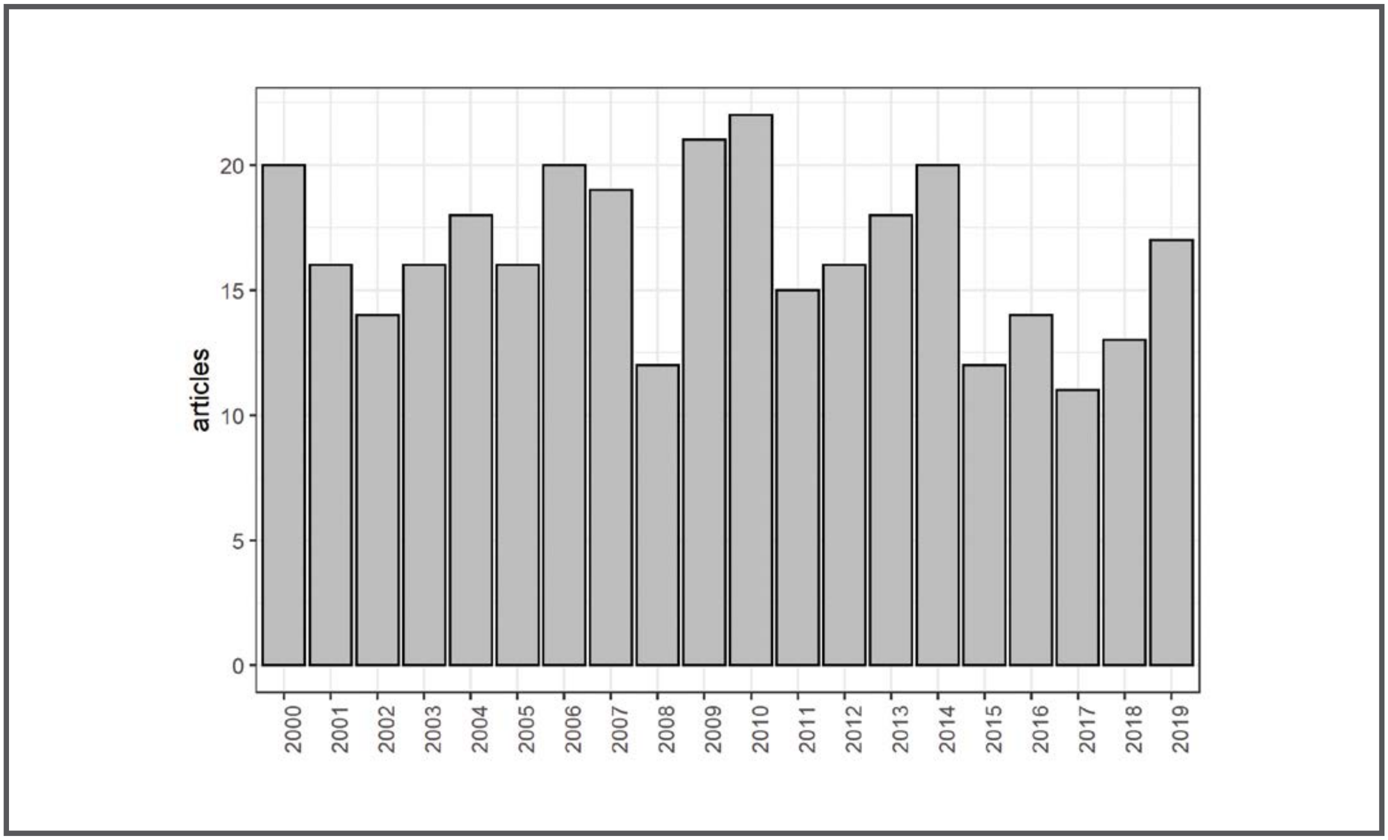


Figure 1. Number of Articles Published by Year

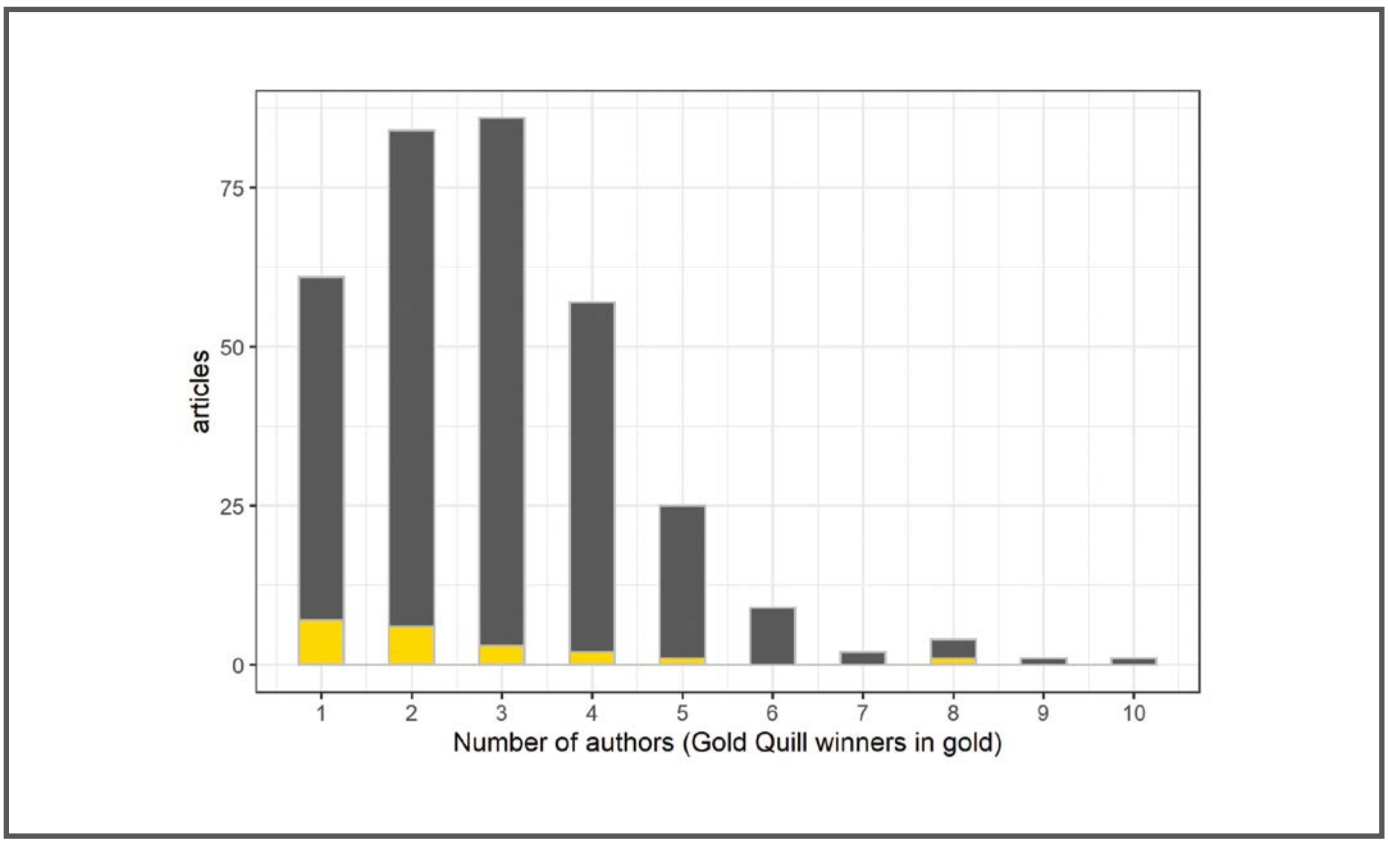


Figure 2. Number of Articles by Number of Authors Since 2000 (Gold Quill Winners in Gold)

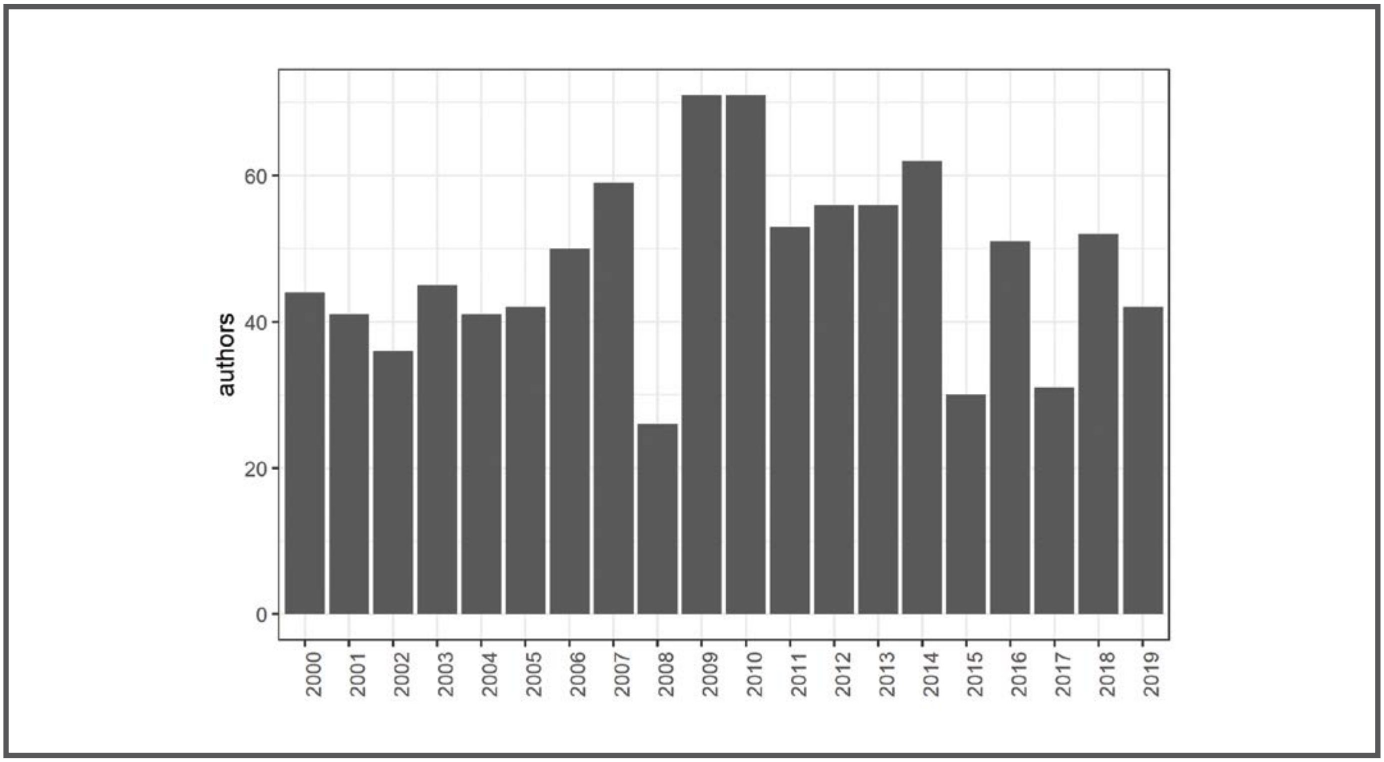


Figure 3. Number of Authors by Year Across All Articles

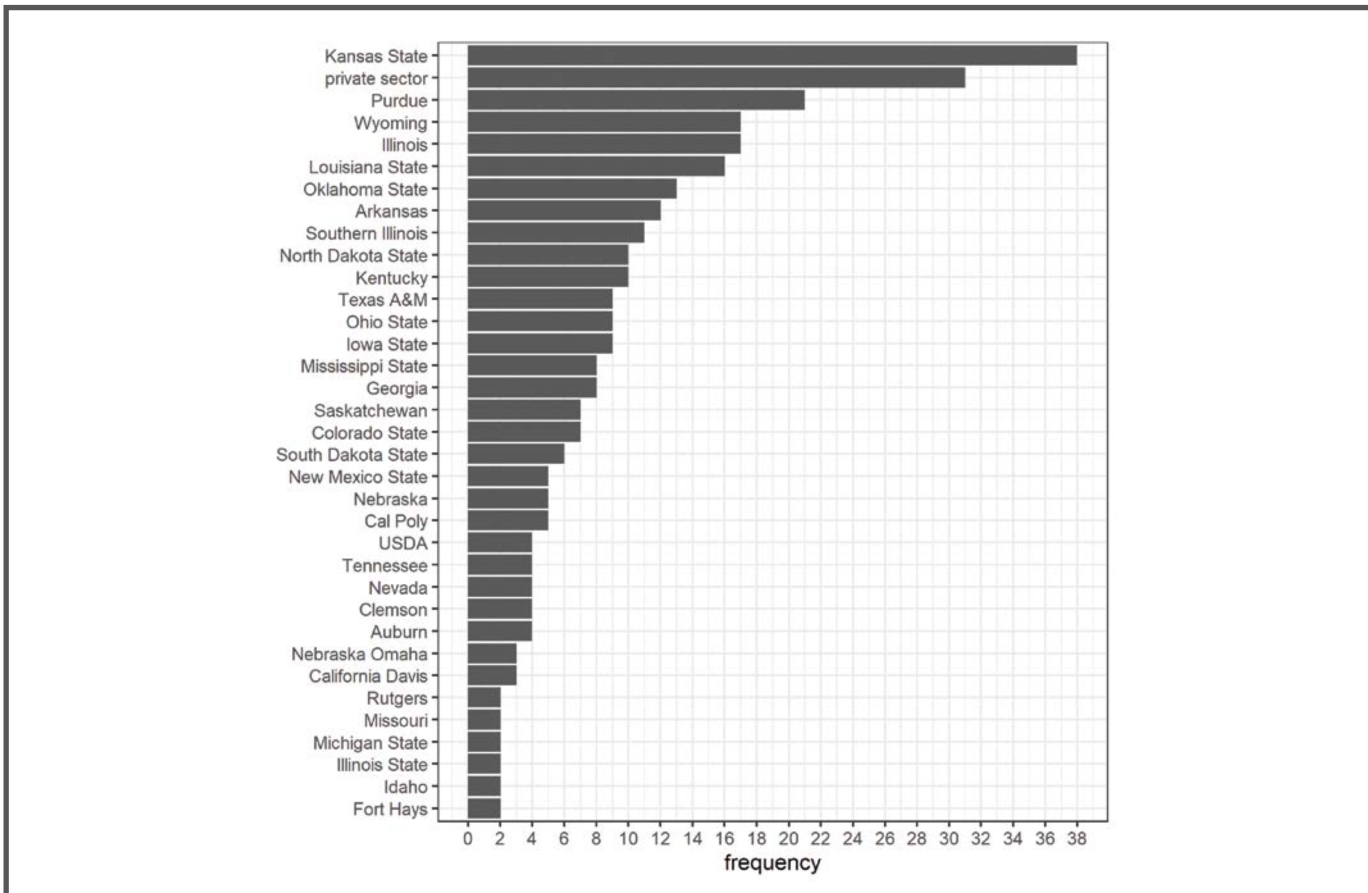


Figure 4. Number of Articles by Institution of Lead Author Since 2000

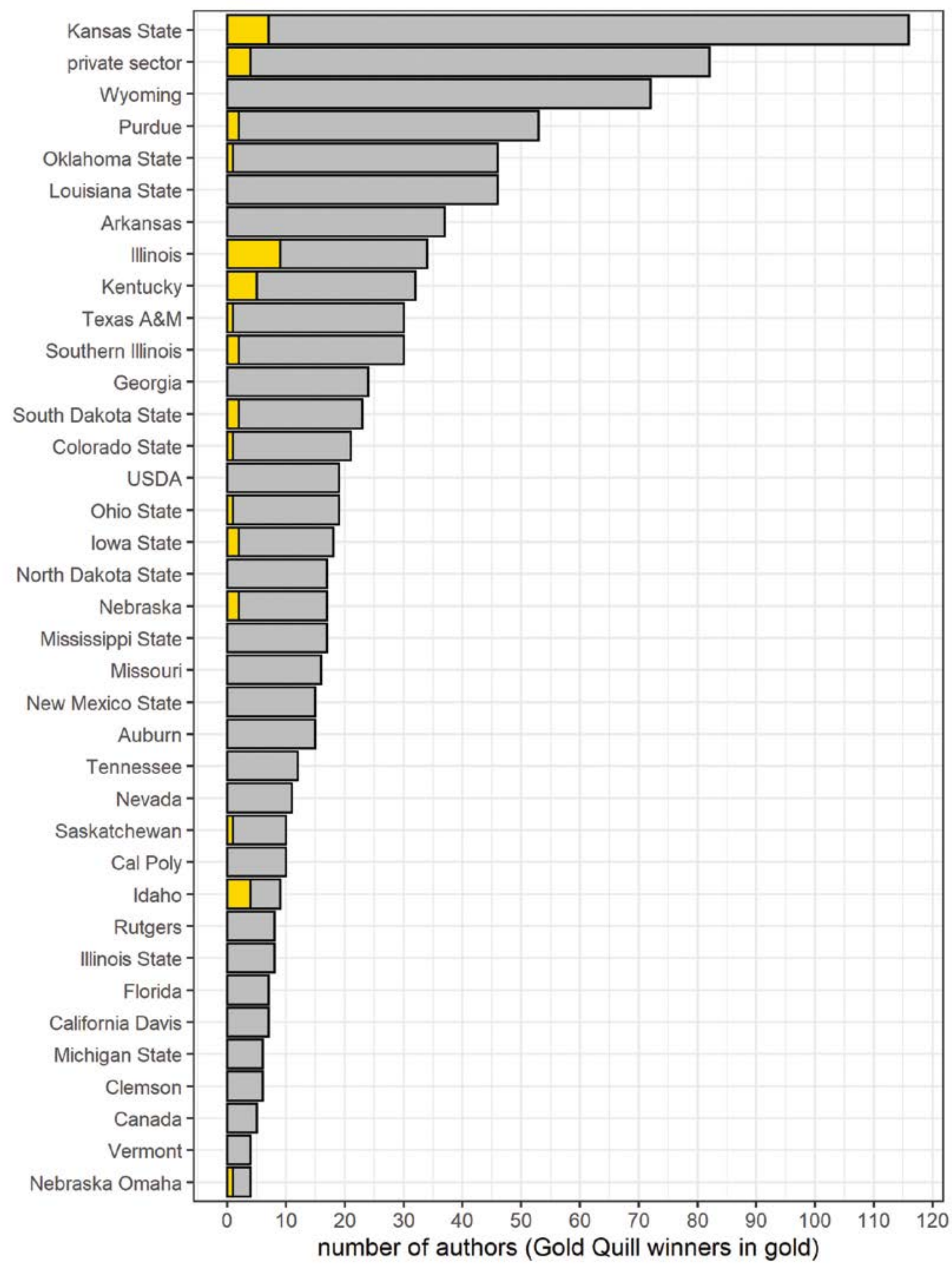


Figure 5. Frequency of All Authors (Including Co-Authors) and Gold Quill Awards by Institution Since 2000

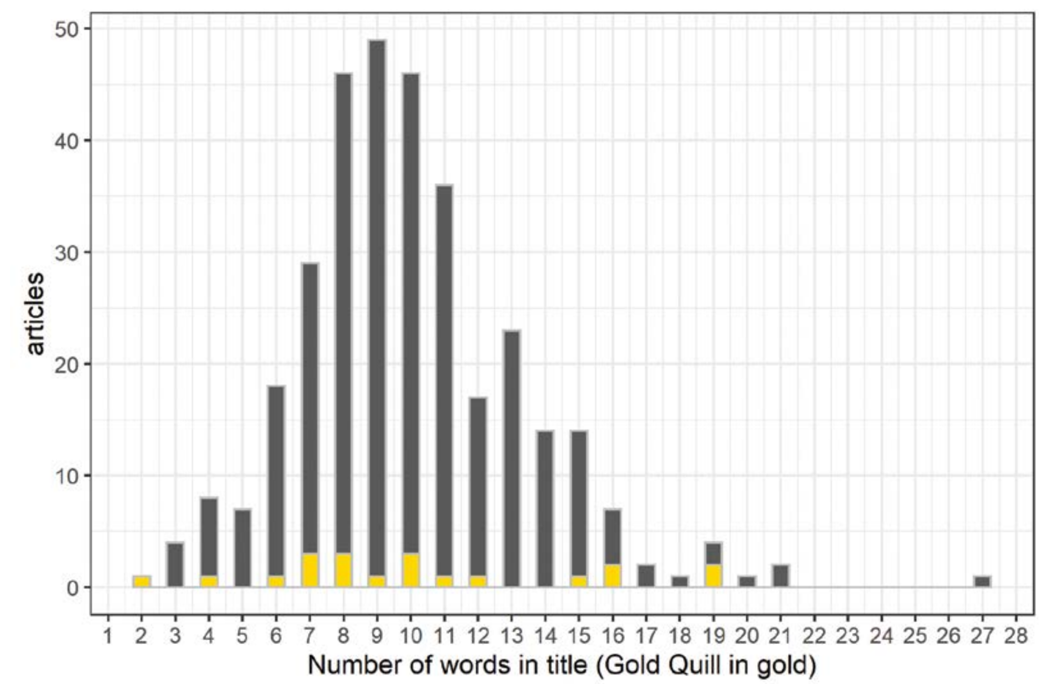


Figure 6. Number of Words in Titles of All Articles and Gold Quill Recipients

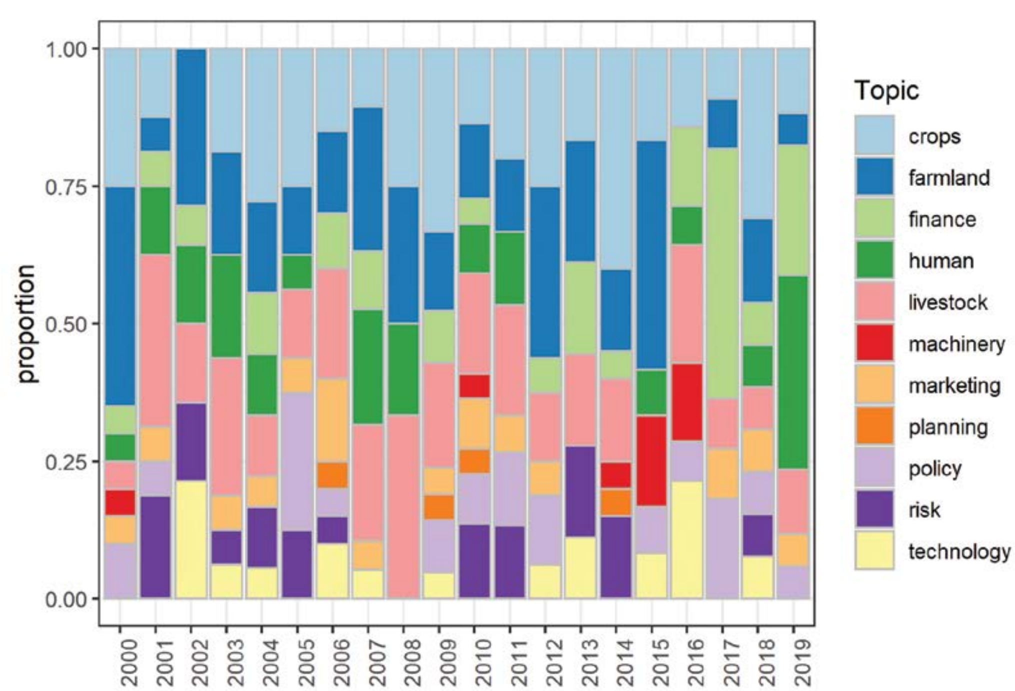


Figure 7. Proportion of Articles by Farm Management Topic by Year

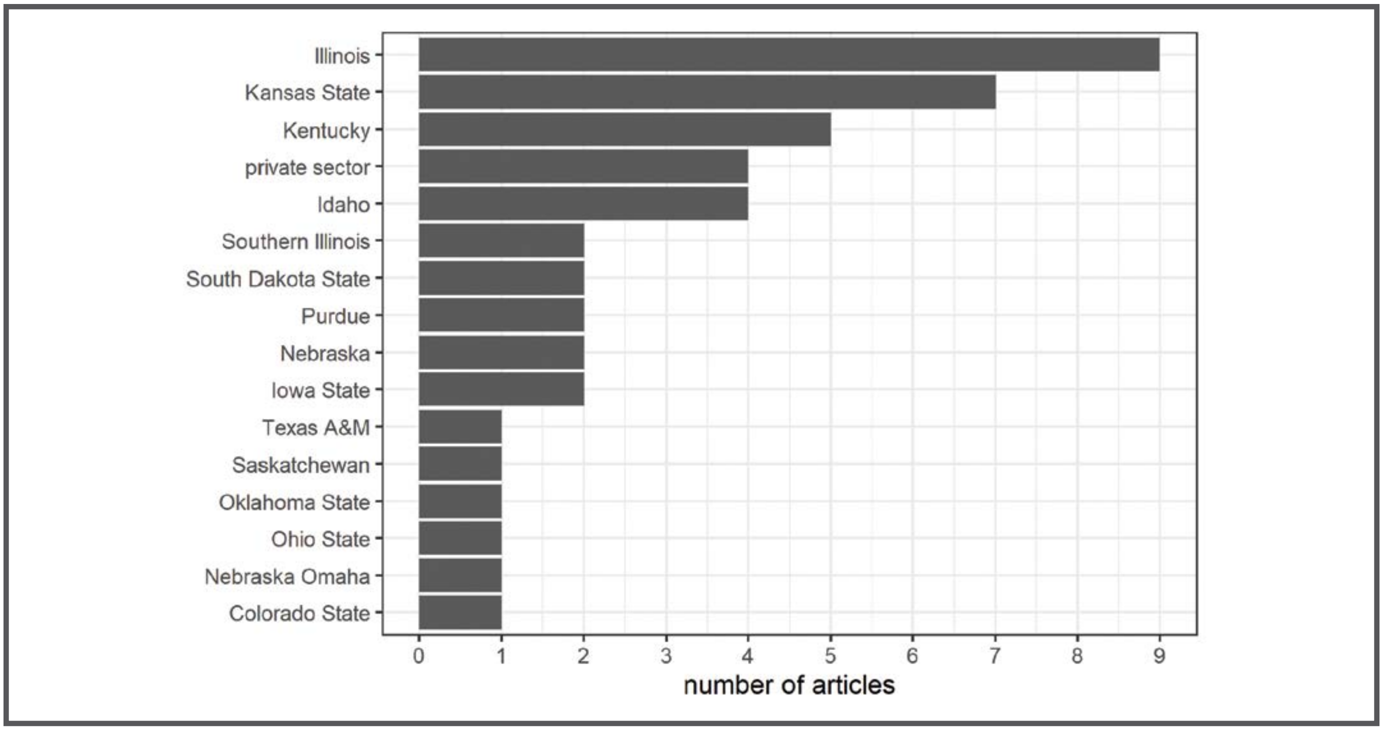


Figure 8. Number of Gold Quill Awards by Institution Since 2000

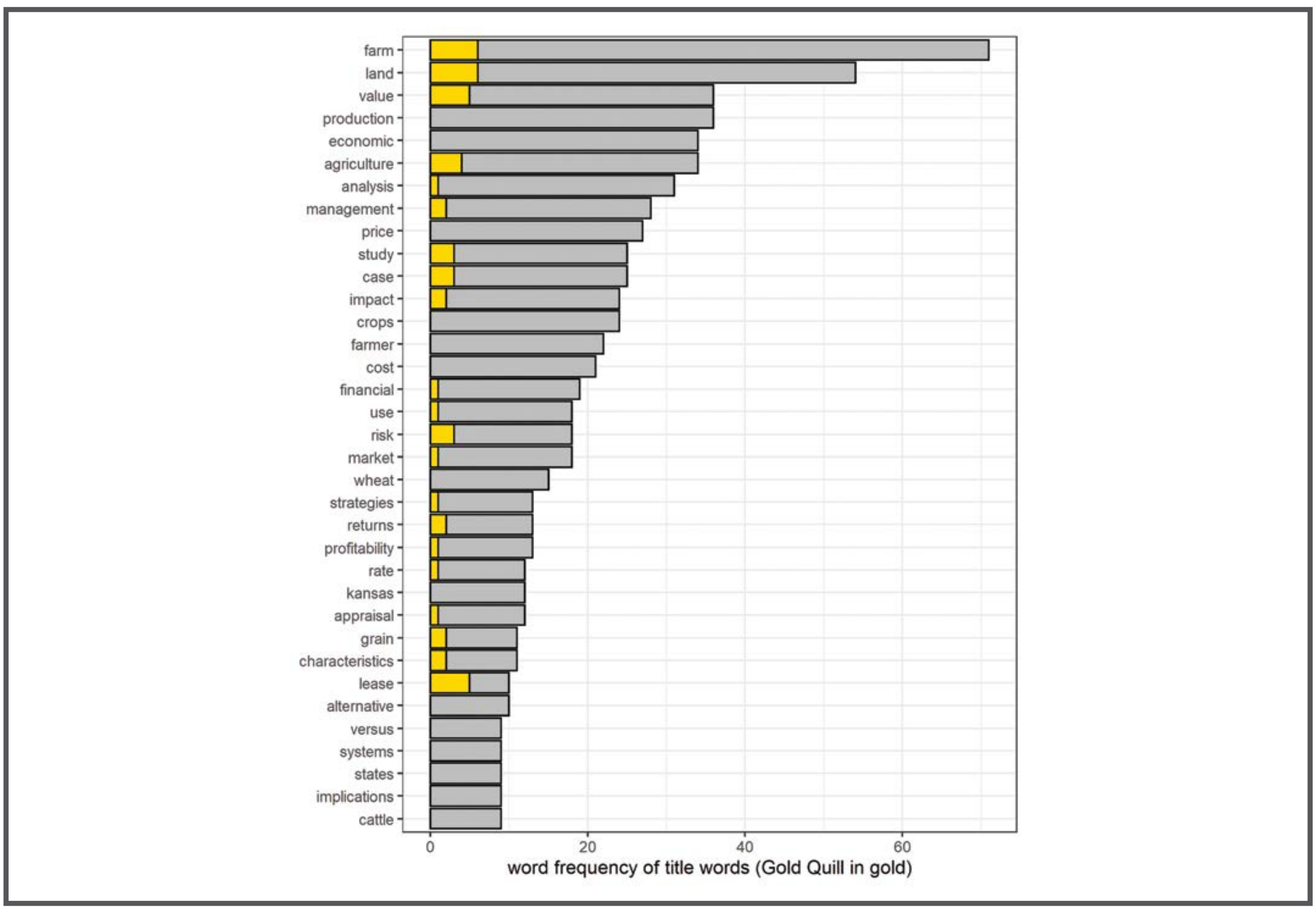


Figure 9. Frequency of Title Words Since 2000 (Gold Quill Winners in Gold)

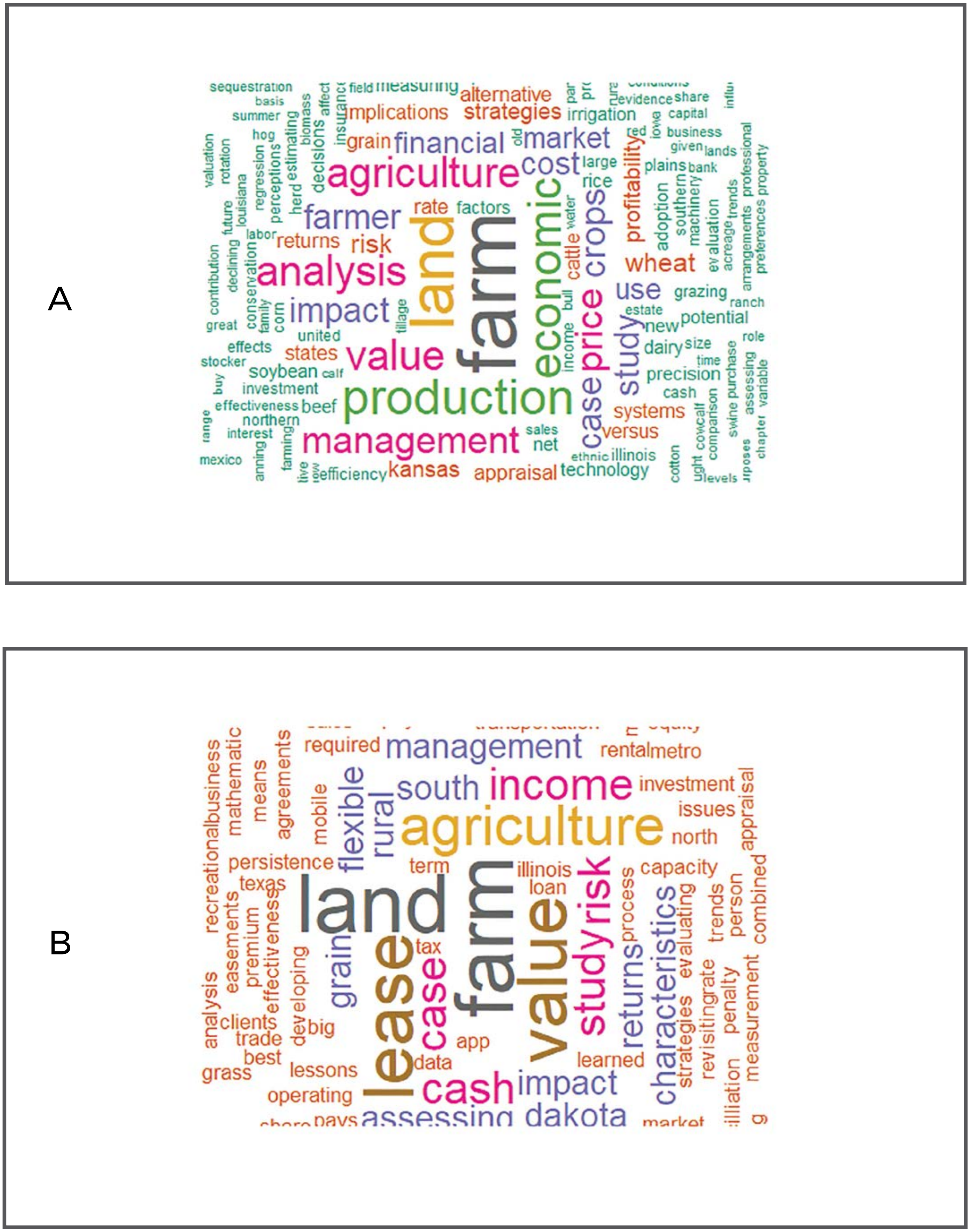


Figure 10A and B. Most Frequent Words Appearing in Titles of ASFMRA Articles by Gold Quill Recipients.
A, Word Cloud of Non-Gold Quill Recipients. *B*, Word Cloud of Gold Quill Recipients.

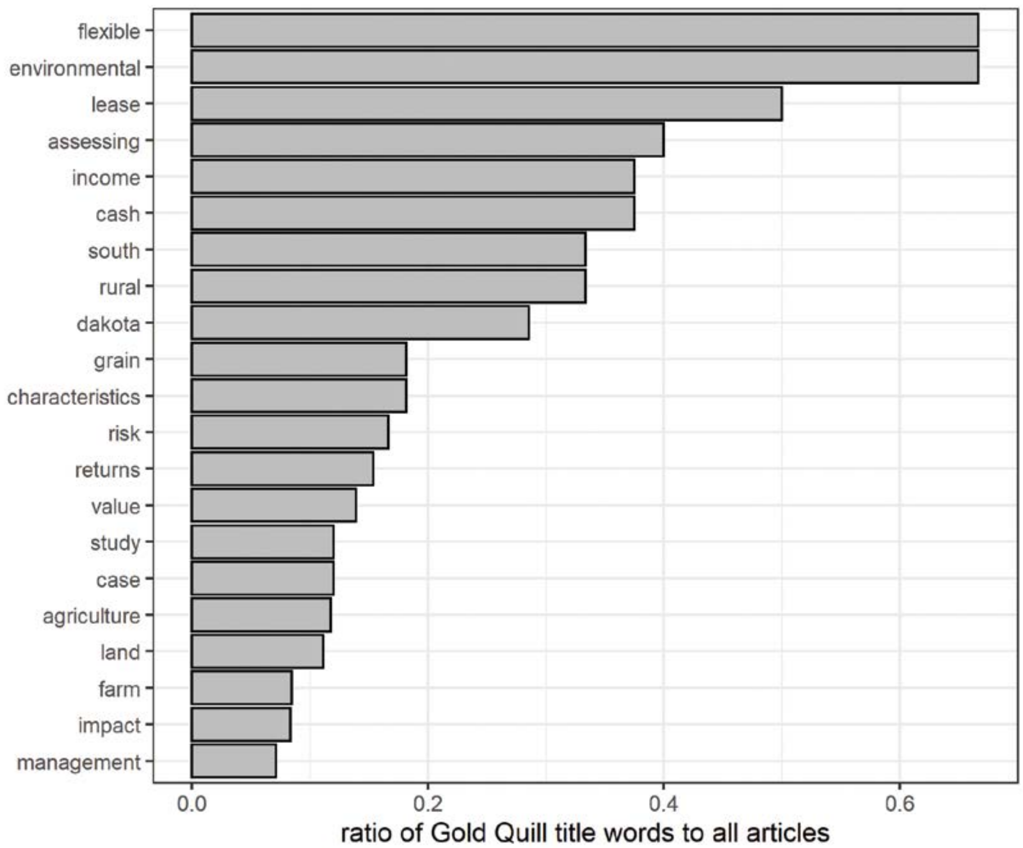


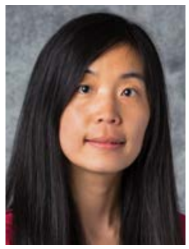
Figure 11. Ratio of Number of Times Title Word Appears in Gold Quill Relative to All Articles (Word Must Appear in at Least Two Gold Quill Titles to Be Listed)

Table 1. Example Set of Word Conversions	
Words Converted From	**Converted To**
agricultural	agriculture
appraisers, appraising	appraisal
banks	bank
benchmarks	benchmarking
changing	changes
costs	cost
crop	crops
easement	easements
economics	economic
farms	farm
farmers, producers, growers	farmer
impacts	impact
farmland	land
leases, leasing	lease
managing, managers	management
marketing	market
prices, pricing	price
producing	production
rates	rate
soybeans	soybean
technologies	technology
using	use
values, valuing	value

Table 2. Number of Articles and Gold Quill Awards by Farm Management Topic, 2000-2019			
Topic	**All Articles**	**Gold Quill**	**Ratio**
crops	65	1	0.02
farmland	52	9	0.17
finance	27	2	0.07
human	28	2	0.07
livestock	54	0	0
machinery	7	0	0
marketing	17	0	0
planning	4	0	0
policy	20	2	0.10
risk	21	2	0.10
technology	15	2	0.13

Agricultural Economic Impacts of Meandering Water and Land Use Changes in the Prairie Pothole Region of South Dakota





By Matthew S. Elliott, Lisa Elliott, and Tong Wang

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Abstract

This study estimates the agricultural economic impact of the land use changes in the Prairie Pothole Region (PPR) of South Dakota. The flooding of wetlands has been documented in this region after 1993. The conversion of non-cropland to cropland has also been observed. We estimate the changes to the agricultural land property tax base and income potential as a result of the land use changes. The purpose is to inform agriculture land assessment and conservation programs.

BACKGROUND

The Prairie Pothole Region (PPR) of the Northern Great Plains covers approximately 560,000 square miles and extends from the north-central United States, including parts of Iowa, Minnesota, North Dakota, South Dakota, and Montana, to the south-central parts of Canada. Most of the region is private land and is used as agricultural land, which is highly productive for small grains, legumes, and livestock.

The PPR is known for its extreme and variable climate and is punctuated by severe droughts and precipitation deluges that influence both the natural and human-dominated ecosystems. Due to substantial long-term precipitation increases starting in 1993, the flooding of wetlands and the formation of larger lakes have occurred in the northern glaciated ecoregions. For example, in the Devils Lake Basin of North Dakota, Stump Lake has increased by 53% in size, and the rural wetland ponds have increased by 426% (Todhunter and Rundquist, 2004). Shapley et al. (2005) also recorded historically unprecedented high water levels in the Waubay Lakes complex in eastern South Dakota in the 1990s. On the semi-permanent and permanent wetlands located in the PPR of North Dakota, McCauley et al. (2015) found that the current surface water areas (2003–2010) were 86% greater than the historical water surface areas (1937–1969). However, the nature of the acres lost, the soil characteristics of the cropland before and after land use changes, and the specific estimates of the economic impact have not been assessed.

Rural wetland flooding, although largely unrecognized, is widespread and can bring extremely harmful effects to the region's agricultural economic base (Todhunter and Rundquist, 2004). To measure and map these changes, remote sensing satellite data is frequently analyzed. Remote sensing has provided high spatial resolution data since 1972 at 16-day intervals by using the Landsat Multispectral Scanner (MSS) and Thematic Mapper (TM).

Despite the rising water in the PPR, additional studies have shown an increasing amount of new cropland. The cropland conversions have raised concerns about the density and connectivity of sensitive wetlands in the area (Johnston and McIntyre, 2019). Furthermore, the increasing cropland conversion of wetlands and grasslands has been attributed to government biofuel policies that have increased the incentives for cropland production (Wright and Wimberly, 2013). Consequently, the changes in land use patterns and surface water may raise difficulties in assessing the highest and best use and marketability of agriculture land in the PPR.

We used remote sensing data from Landsat satellites to estimate the land use changes and most probable use of land in the region. We found that the number of cropland acres has increased in the region by approximately 550,000 acres despite the additional flooded areas. We estimated that much of the new cropland was converted from non-cropland that was likely considered hayland previously. We estimated that there was only a small shift in acres (approximately 40,000) that was surface water in the 1990–1992 period but later converted to cropland. We also estimated the difference in net income and revenue on the new areas of cropland for a corn and soybean rotation compared to using the same area as pastureland for cattle during the 2008–2017 period. We found that the new cropland acres averaged approximately $80 per acre more in revenue for a corn and soybean rotation than pastureland. However, we estimated that the average net income was $12 per acre less on the new cropland acres during the 2008–2017 period when the land was used in a corn and soybean rotation compared to pastureland. Despite our expectations of lower net income for cropland compared to pastureland, we found that there is a high probability (79%) that the new cropland areas will continue to be used mostly as cropland. Given the increased number of acres of cropland in the area with boosted expected revenue, we did not find that the meandering waters have caused severe losses to the economic base of the area. Indeed, most of the acres are still highly anticipated to be used as cropland due to the potential to increase expected revenue in the near future.

METHODS

To detect the locations of the land use changes in this study, we used the most straightforward method of comparing land cover classifications from two three-year periods (e.g., 1990–1992 and 2016–2018). For each study period, we collected all Landsat images that were below 10% cloud cover during the months of May and June—typically the wettest period for the area where surface water extents are at their peak. After removing pixels in the images for low-quality pixels and development areas, we then classified the remaining pixels by using a random forest classifier. We classified the pixels into three land use categories: (i) cropland, (ii) non-cropland, and (iii) water. To classify the pixels, we used the maximum modified water index (Xu, 2005) and the maximum normalized differentiation vegetation index (NDVI).

The method used to estimate the economic loss and soil quality of the land use changes is based on the area of land use change (i.e., the net loss acreage of cropland and non-cropland) and data from the USDA National Resources Conservation Service (NRCS) soil database, spatial weather data (PRISM), digital elevation maps, and the USDA National Agricultural Statistics Service (NASS) county reported yields that we extrapolated to each soil map unit. We used the aforementioned data to predict expected cropland and grassland yields, expected animal unit month (AUM) carrying capacity, economic returns, and probability of being used as cropland for each soil map unit in the area with a random forest regression model (Elliott et al., 2019). We then estimated the mean revenue per acre expected to be generated by land use conversion, using the state annual prices received data from the USDA-NASS for planting corn and soybeans compared to using the land for pastureland with cattle. The costs to derive a net income difference between cropping the area and using the land for pastureland were based on South Dakota State University (SDSU) enterprise budgets (Davis, 2017; Gessner, 2017), and adjustments were made using USDA-NASS cost indexes. We also calculated the mean crop productivity index (CPI) and land capability classifications (LCCs) (Klingebiel, 1958) based on the land use change for the study region and each county in the study area.

We report the differences in cropland and cattle pastureland revenue per acre and net income per acre for the land use changes. We also report the probability that the studied areas are used mostly as cropland. Lastly, we report the loss to the property tax base by using the acres lost to water and the current assessment method based on the South Dakota agricultural productivity property tax formula. Under South Dakota law, when agricultural land becomes inundated with water for three or more years, the land can be reassessed with the county's water assessment.

FINDINGS

Cropland and Non-Cropland Acres Lost to Surface Water

We found that there were approximately 140,000 cropland and non-cropland acres lost to surface water in the 13-county region (Figure 1) between the two time periods (Figures 2 and 3).

New Cropland Acres

We also found that approximately 40,000 acres that was surface water in the 1990–1992 period was subsequently converted to cropland by 2016–2018 (Figure 4). Similar to other research, we found that net new cropland acres increased by approximately 550,000 acres (Figure 5). The estimate of net new cropland acres is a sum of the acres that were converted from non-cropland and surface water minus the acres that were cropland but were converted to non-cropland or became flooded (Table 1). Our estimates of cropland increases in the region are higher than the changes that have been reported in the USDA Census of Agriculture for 1992 and 2017 (Figure 5). The higher number of net new cropland acres that we estimated may be partly attributed to the acres that we classified as non-cropland during the 1990–1992 period using the Landsat imagery that were hayland and reported by producers as cropland. Hayland is difficult to distinguish in Landsat imagery from non-cropland that largely consists of pastureland, although it is typically identified as cropland by the USDA-NASS (2008–2017).

Land Use Changes and Soil Quality

Generally, we found that cropland in the 1990–1992 period was of lower quality than the area that was cropland from 2016–2018 according to the USDA-NRCS soil ratings. That is, cropland changes on net have improved the overall quality of the cropland between the two periods. This is partly because the areas of cropland that were lost to water were generally of a lower quality, and the areas that have experienced conversions of cropland to and from non-cropland appear to be of similar quality. Specifically, over the entire study area, the mean CPI of the cropland in 1992 was 72.33. This is lower than the mean CPI of 73.19 for the cropland in the same study area in 2018 (Table 2). The relationship was the same when we used the LCC: The cropland improved from a mean LCC of 2.49 to 2.43 (a lower LCC indicates that soils have fewer limitations and management problems). This change can be understood in a way that the new areas of cropland were generally better than the areas of cropland that then returned to non-cropland.

Additionally, we found that the cropland areas that became inundated with water had a much lower mean CPI (38.39) and a higher LCC (4.60) (Table 2). For the new cropland areas, we found that only 12% had an LCC of 5 or greater—which signifies that there are soil attributes that would present significant management problems for cropland—and 30% that had an LCC of 4 or greater, with an LCC of 4 indicating that the land can be cropped but with attributes that make it more difficult according to the NRCS (Table 2). Thus, more than 70% of the new cropland areas are on soils that have minimal management limitations and are generally suitable for cropland production. Moreover, we found that for the newly converted cropland, the percent of soil that is subject to ponding was only 11% (Table 2). The new cropland areas have a lower quality than the cropland areas that persisted through the studied time period; however, the persisted cropland areas had a mean CPI of 73.78. The new cropland areas are less prone to flooding than the acres that were previously lost.

Estimated Revenue and Net Income

Using a model that incorporates USDA-NASS reported county yields, USDA-NRCS soil and crop production attributes, and in-season climate data, we estimated the expected amount of revenue by land use change when the land is used for soybeans, corn, or pastureland in 2017 in Table 3. We estimated that there is no difference in the corn revenue per acre ($356) between the acres that were cropland during the 1990–1992 period and the acres that were cropland during the 2016–2018 period. However, the soybean revenue per acre for the earlier period is predicted to be slightly higher ($409 per acre).

In all land use cases, the revenue from a corn and soybean rotation is predicted to be greater than the revenue that could be gained from using the land as pastureland. The difference in mean revenue per acre during the 2008–2017 period is shown in Figure 6. For example, areas in yellow in Figure 6 indicate that the estimated mean revenue for land used in a corn and soybean rotation was $66.72 to $85.12 higher compared to pastureland for cattle. However, despite the higher revenue that can be obtained from a corn and soybean rotation, a large portion of the area is estimated to have less net income when used in a corn and soybean rotation (Figure 7). For example, the area indicated in orange in Figure 7 shows where the land used in a corn and soybean rotation was expected to have a net income of $68.36 to $33.49 per acre less than using the land as pastureland for cattle during the 2008–2017 period. Specifically, we estimated that the cropland areas that were converted from non-cropland (indicated by the brown hue in Figure 2) had a mean revenue per acre of $80.92 higher when used in a corn and soybean rotation than when used as pastureland; however, corn and soybean rotation resulted in a mean net income that was $11.92 less than using the land for pastureland (Table 4). A caveat is that the reported net income differences are based on uniform assumptions of enterprise budget costs produced by SDSU that may not accurately reflect actual costs by producers in the region, and the revenue is based on USDA-NASS annual state average prices received that may not reflect actual prices producers in the region received for their production.

Probability of Cropland Use

When using an economic model that incorporates topography, USDA-NRCS soil ratings, climate, and the expected cropland revenue and net income of common land uses, we estimated the probability that land will be used as cropland given observed use patterns in the region. For most areas in the study region we found that the probability of being used mostly as cropland is high. For example, the green areas indicated in Figure 8 have a greater than 64.5% probability of being used mostly as cropland. Alternatively, the red areas have less than a 14.11% probability of being used mostly as cropland. Despite the lower estimated net income for corn and soybeans compared to pastureland on the acres of newly converted cropland, we found that the mean probability of being used mostly as cropland is approximately 79% (Table 4).

Economic Impact of Rising Waters

To estimate the lost agricultural value from the rising water, we can take the per acre revenue estimates and multiply them by the land use changes. For example, Day County was found to have the most acres lost to water (59,178). Of these lost acres, approximately 11,000 acres were cropland. In addition, we estimated that the lost cropland acres were generally of high quality in Day County, where the predicted corn revenue in 2017 was $381 per acre and the soybean revenue was $487 per acre. For example, if we average the corn and soybean revenue per acre values, assuming that an equal rotation would have been planted on the lost acres, and multiply the average revenue by the estimate of the lost cropland acres to water in Day County, then the lost revenue per acre because of rising waters is approximately $4.8 million in 2017 in Day County. Furthermore, using the same method for the entire study area, the lost revenue from the cropland lost to water (approximately 35,000 acres at $403 per acre) would result in a lost cropland revenue of $14.1 million in 2017. If we then multiply the non-cropland acres lost to water in the study area (105,000 acres) by the predicted revenue from pastureland ($157 per acre), we can estimate a loss of non-cropland revenue of $16.5 million in 2017 for the whole study area. Taking account of the lost cropland and non-cropland areas in the entire study area, the estimated lost agriculture revenue is approximately $30.6 million in 2017.

Lastly, we estimated the lost agriculture property tax base due to rising waters. We found that the expected change in the property assessment for cropland acres in the study area that became inundated was approximately $25.7 million in 2017. We also found that the lost assessment to non-cropland acres that became inundated was approximately $45 million (Table 5). Thus, over the entire study area, we estimated that the agriculture property tax base was $71 million dollars less than it would have been if the surface water levels were similar to the surface water levels in the 1990–1992 period. Day and Clark Counties were expected to have the largest loss in the agricultural property tax base because of the rising water; specifically, the loss was estimated to be $11.2 million and $13.8 million, respectively, in 2017.

Currently, South Dakota's property tax policy for assessments is not based on the current use of the property but on the LCC from the USDA-NRCS. Thus, non-cropland that is converted to cropland does not increase the agricultural property tax base. Similarly, cropland that is converted to grassland does not reduce the agricultural property tax base. There are only changes to the agricultural property base when there are areas of soil, not already indicated by the USDA-NRCS to be water, that become inundated for three years or longer; this is when the possibility exists that an adjustment to the assessments will occur.

CONCLUSION

The findings of our study indicate that there has been a sizable number of acres lost to rising water in the PPR of South Dakota from 1990 until present day. These rising waters appear to have had the greatest impact on Day and Clark Counties but were observed to lesser degrees in the other counties we examined as well. At the same time, we also observed an increased number of cropland acres in the region, most of which were converted from previous non-cropland or hayland. We estimate that the gross revenue generated on the new cropland acres was approximately $80 per acre higher than would be obtained as pastureland for cattle during the 2008–2017 period; however, we also estimate that the net income is approximately $12 per acre less when used in a corn and soybean rotation during the same period. Despite the lower estimated net income, we find that the new cropland areas are expected to be used mostly as cropland in the near term. As a whole, the new cropland areas are of a higher quality than the cropland acres that were lost. Furthermore, the new cropland acres appear to be less prone to flooding and are largely in areas that are capable of crop production with minimal management limitations, according to the USDA-NRCS. As a result, we find that over the study area, agriculture revenue has increased in the region because of land use changes despite rural flooding. However, we do not find evidence that overall net income to agriculture producers has necessarily improved. Lastly, we do estimate that the property tax base has decreased because of the rising waters in the region.

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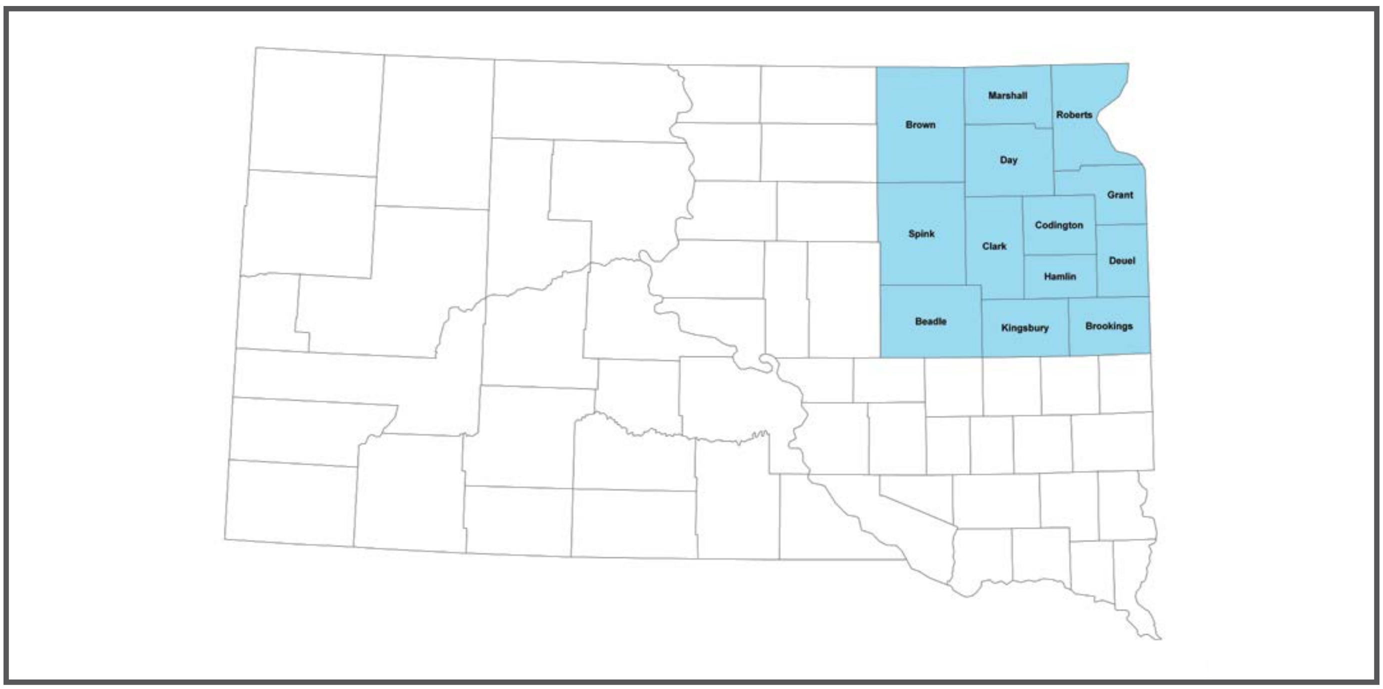

Figure 1. South Dakota Study Area

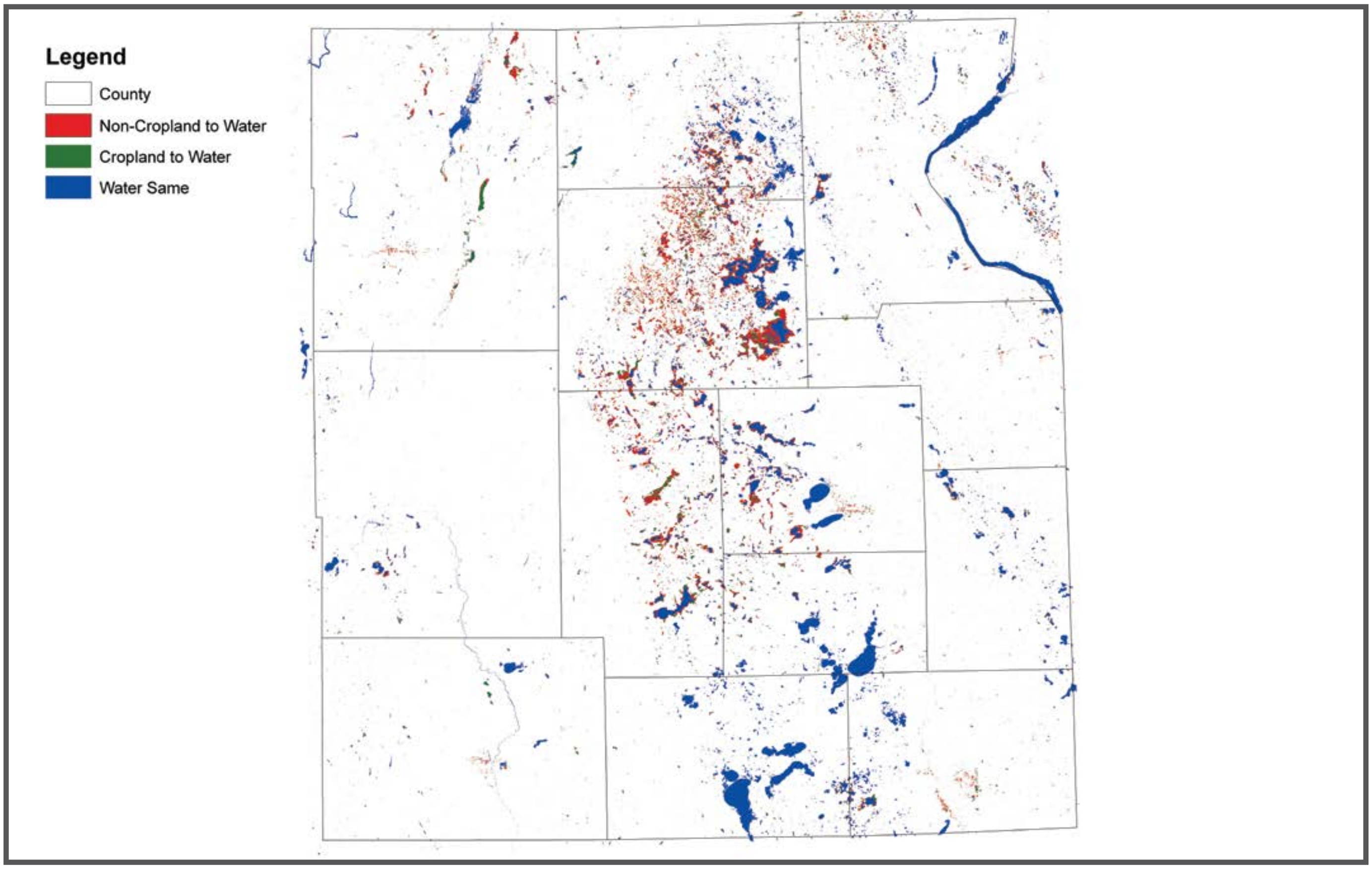

Figure 2. Changes to the Surface Water in the South Dakota PPR

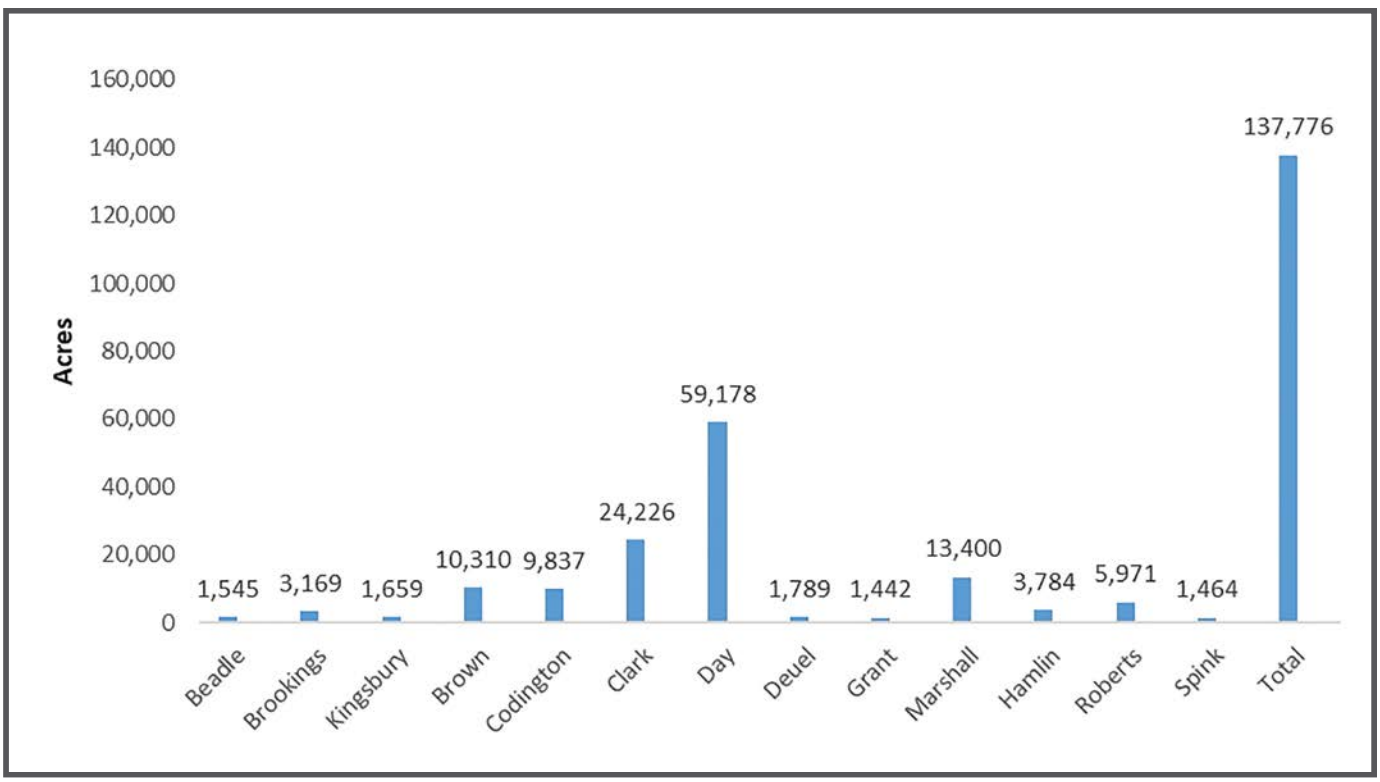

Figure 3. Cropland and Non-Cropland Acres that Changed to Water

Figure 4. Northeast South Dakota Water and Non-Cropland Acres that Changed to Cropland

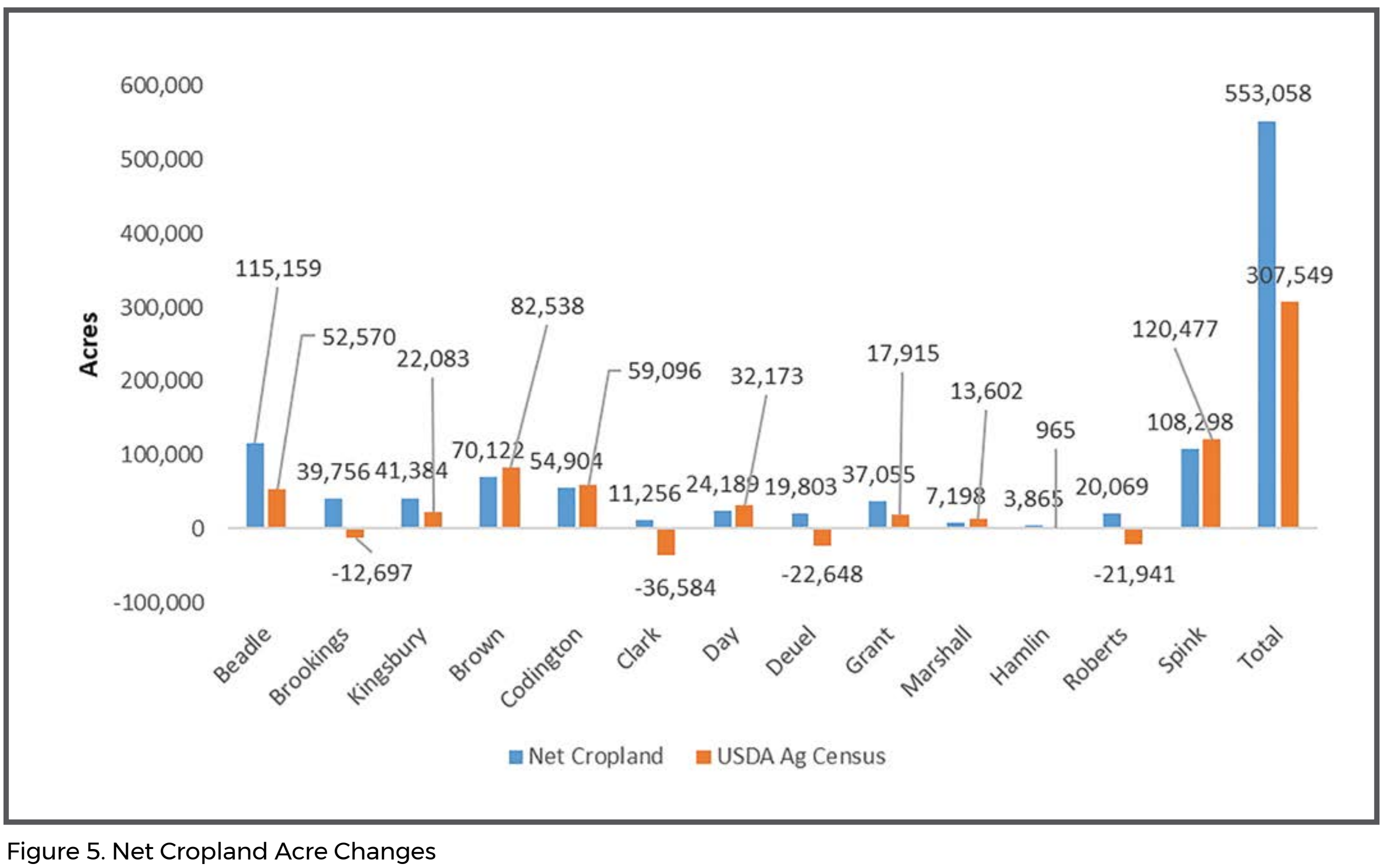

Figure 5. Net Cropland Acre Changes

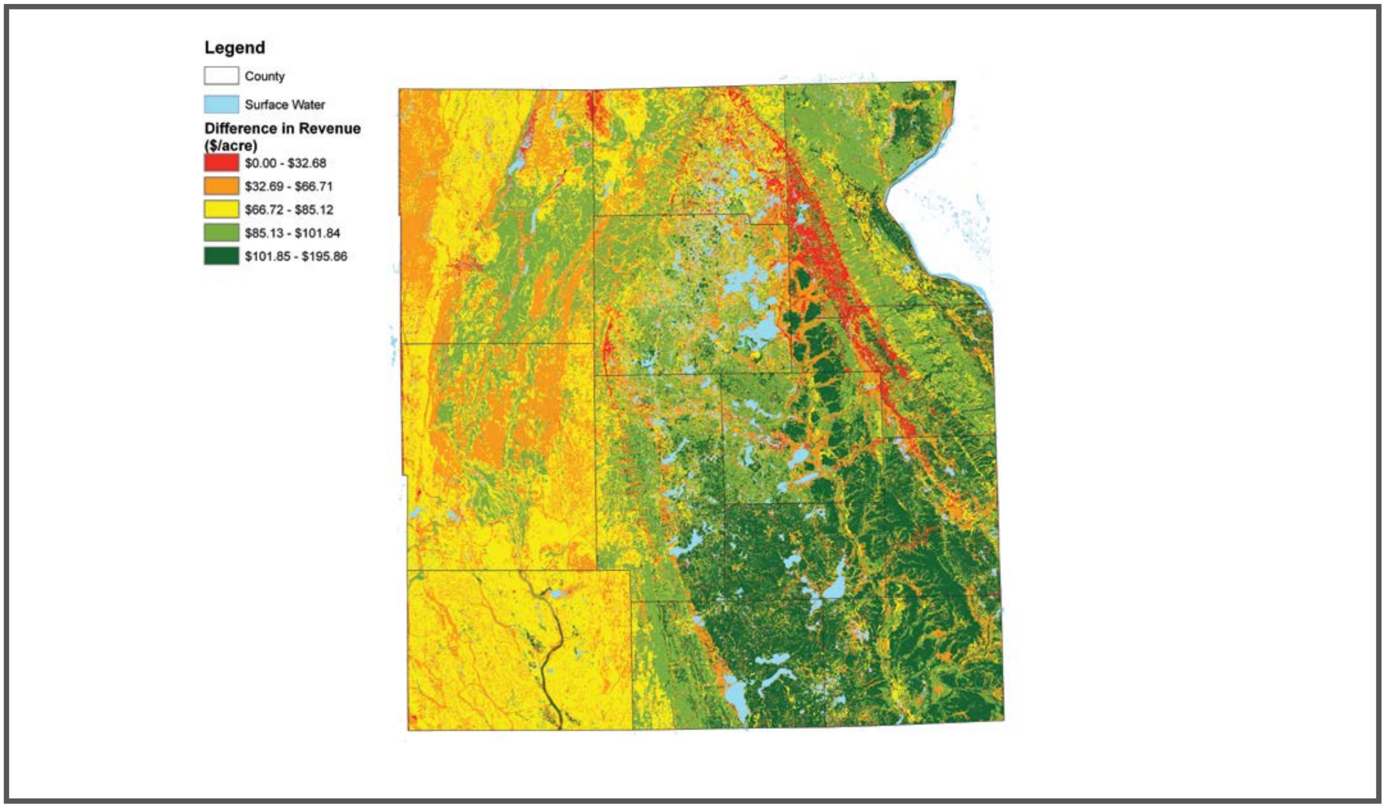

Figure 6. Mean Revenue Difference ($/acre) Between Corn and Soybean Rotation and Pastureland for Cattle (2008–2017)

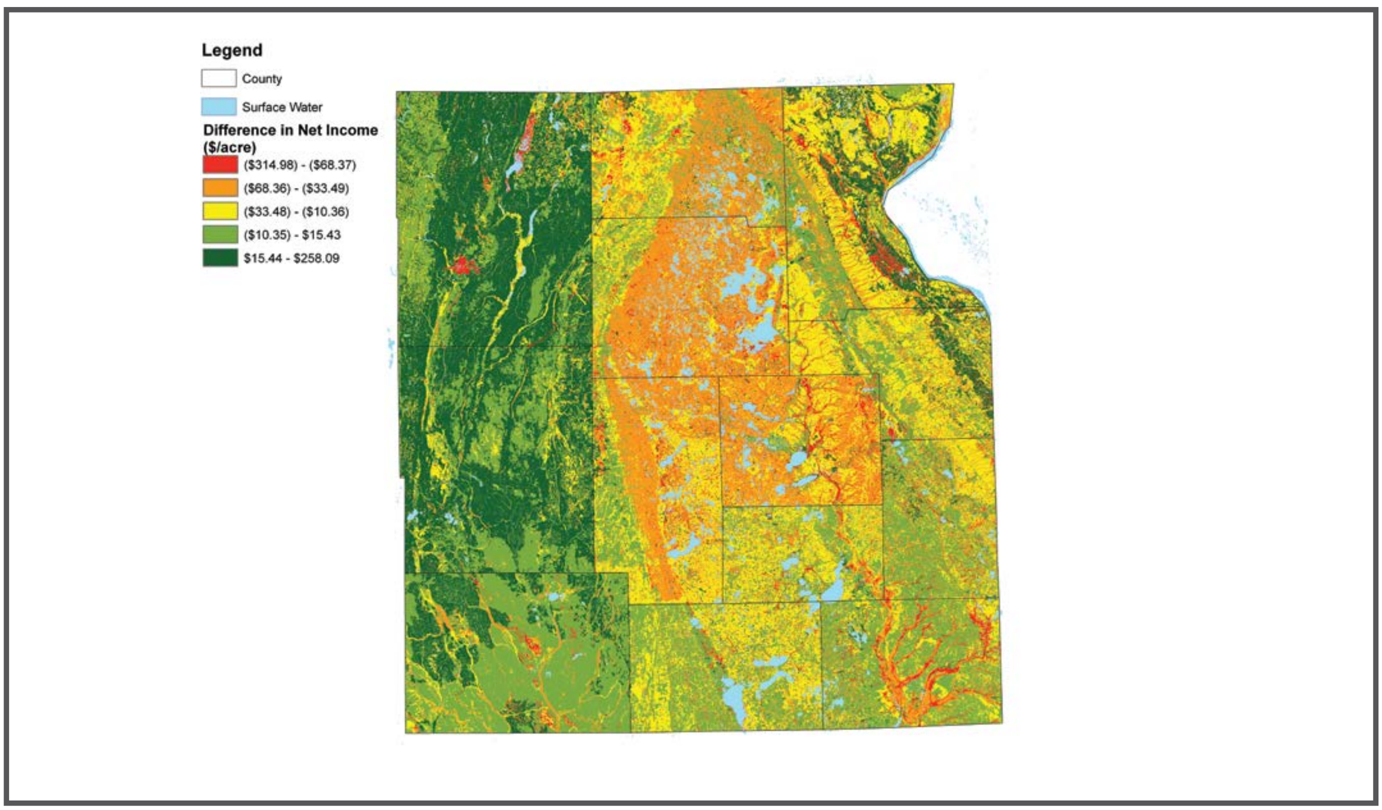

Figure 7. Mean Net Income Difference ($/acre) Between Corn and Soybean Rotation and Pastureland for Cattle (2008–2017)

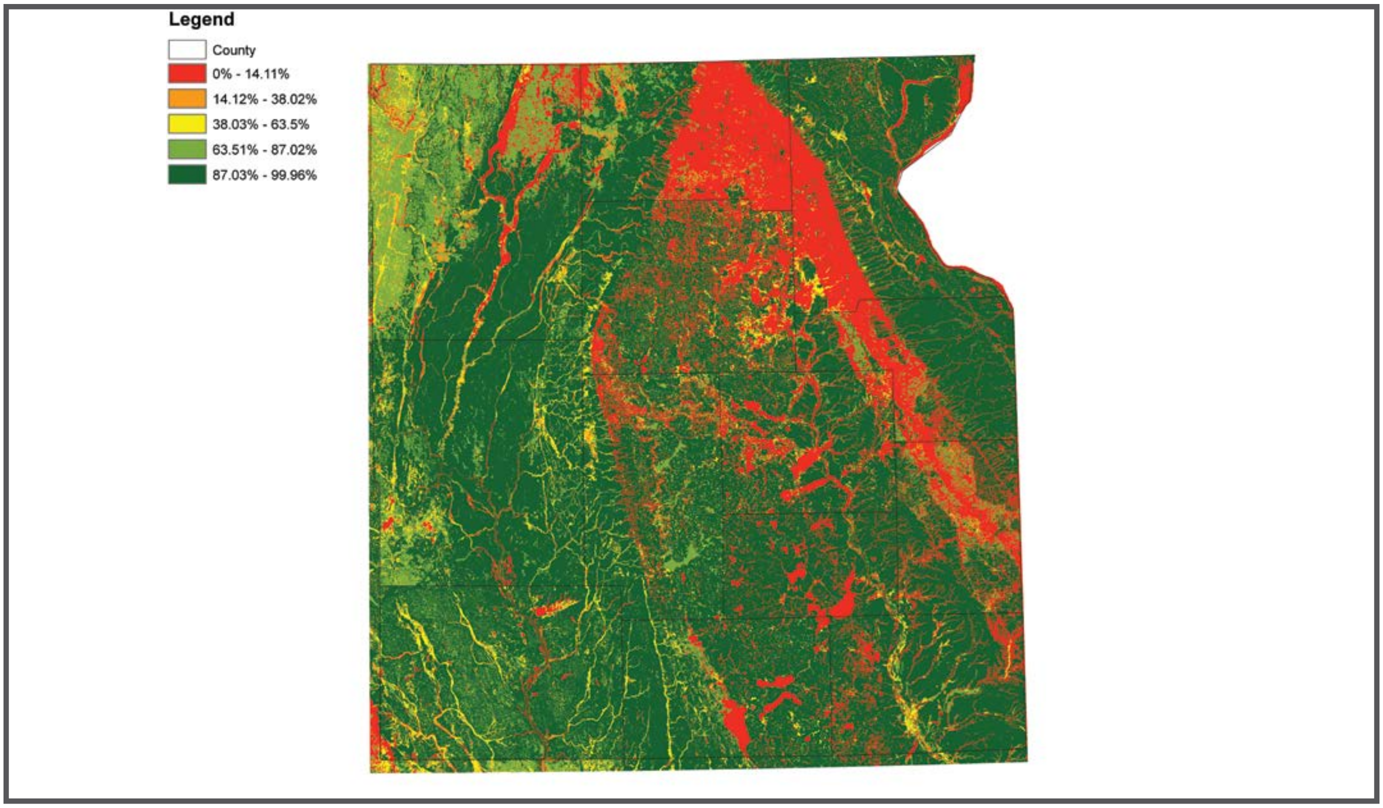

Figure 8. Probability of Agriculture Land Being Used Mostly as Cropland

Table 1. Land Use Acre Change for Northeast South Dakota Counties

Land Use Change (Acres)	Beadle	Brookings	Kingsbury	Brown	Clark	Codington	Day	Deuel	Grant	Hamlin	Marshall	Roberts	Spink	Total
Crop Same	352,345	255,822	292,946	579,580	277,089	229,831	268,012	181,725	220,281	198,002	209,567	336,505	586,793	3,988,498
Non-Cropland to Crop-land	152,311	67,409	63,474	146,377	92,827	39,333	77,856	41,746	50,905	27,595	46,125	62,692	129,208	997,859
Non-Cropland Same	203,723	111,706	94,429	204,438	156,205	109,488	166,266	131,171	135,469	53,283	203,673	204,539	155,271	1,929,659
Cropland to Non-Cropland	41,553	26,997	24,927	78,273	32,725	26,663	44,591	21,696	13,755	20,245	41,231	43,566	31,942	448,163
Non-Cropland to Water	516	1,917	882	5,740	17,615	7,829	48,233	1,395	992	2,376	10,834	4,187	1,002	103,520
Water to Non-Cropland	8,653	2,637	9,164	15,497	2,674	2,972	5,256	1,898	1,825	4,542	5,573	11,697	12,956	85,344
Water Same	4,546	11,155	38,538	12,198	17,819	23,341	43,305	8,417	3,220	22,875	21,727	18,502	5,852	231,495
Cropland to Water	1,029	1,251	777	4,570	6,611	2,008	10,945	393	451	1,408	2,566	1,784	461	34,256
Water to Cropland	5,429	595	3,614	6,588	1,412	594	1,869	146	356	1,257	1,537	2,727	11,494	37,617

Table 2. Mean CPI, LCC, and Ponding Frequency by Land Use Change

Mean CPI	Study Area	Beadle	Brookings	Kingbury	Brown	Clark	Codington	Day	Deuel	Grant	Hamlin	Marshall	Roberts	Spink
Lost Cropland	60.82	58.57	62.47	66.47	58.23	57.43	62.29	59.1	64.87	62.86	63.47	58.99	66.06	57.9
New Cropland	63.66	65.73	63.57	66.73	60.32	67.37	69.14	59.32	67.06	64.54	69.22	62.91	63.46	59.41
Same Cropland	73.78	70.68	72.34	69.7	74.12	75.14	77.35	73.91	76.49	70.5	77.93	64.89	72.19	73.68
Cropland Lost to Water	38.89	56.89	57.21	43.5	34.79	30.24	26.4	49.1	32.51	53.19	30.39	29.82	41.54	45.03
Cropland 1990–1992	72.33	69.27	71.04	69.34	71.86	73.63	75.99	70.33	75.69	70.04	76.33	61.77	69.67	73.05
Cropland 2016–2018	73.19	70.22	71.44	69.38	73.22	75.26	77.96	73.12	76.26	70.07	78.56	69.36	69.71	72.57
Mean LCC	**Study Area**	**Beadle**	**Brookings**	**Kingbury**	**Brown**	**Clark**	**Codington**	**Day**	**Deuel**	**Grant**	**Hamlin**	**Marshall**	**Roberts**	**Spink**
New Cropland	2.99	2.84	2.99	2.73	3.18	2.77	2.54	3.31	2.86	2.9	2.76	3.3	3.04	3.18
Lost Cropland	3.16	3.25	2.86	2.87	3.42	3.46	2.86	3.19	2.86	2.87	3.04	3.38	2.84	3.36
Same Cropland	2.4	2.51	2.32	2.48	2.54	2.29	2.04	2.47	2.22	2.44	2.12	2.93	2.4	2.54
Cropland Lost to Water	4.6	3.13	3.05	4.37	5.27	5.79	5.63	3.72	2.68	2.83	5.74	4.05	4.1	4.36
Cropland 1990–1992	2.49	2.6	2.39	2.52	2.67	2.39	2.12	2.65	2.27	2.47	2.22	3.17	2.58	2.57
Cropland 2018	2.43	2.55	2.42	2.49	2.56	2.27	2.01	2.56	2.25	2.48	2.09	2.84	2.59	2.58
	Study Area	**Beadle**	**Brookings**	**Kingbury**	**Brown**	**Clark**	**Codington**	**Day**	**Deuel**	**Grant**	**Hamlin**	**Marshall**	**Roberts**	**Spink**
New Cropland Percent with LCC 5 or Greater	0.12	0.07	0.15	0.09	0.11	0.09	0.09	0.25	0.14	0.1	0.14	0.13	0.07	0.16
New Cropland Percent with LCC 4 or Greater	0.29	0.26	0.27	0.21	0.36	0.26	0.15	0.39	0.26	0.25	0.22	0.37	0.29	0.33
New Cropland Percent of Soil Map Unit that is Subject to Ponding	0.11	0.1	0.04	0.11	0.16	0.1	0.07	0.1	0.06	0.06	0.07	0.09	0.07	0.15
Lost Cropland Percent of Soil Map Unit that is Subject to Ponding	0.19	0.14	0.04	0.17	0.29	0.28	0.17	0.19	0.07	0.1	0.17	0.22	0.15	0.19

Table 3. Mean Corn, Soybean, and Pastureland Revenue Per Acre ($/acre) for Northeast South Dakota Counties

2017 Mean Corn Revenue Per Acre	Study Area	Beadle	Brookings	Kingbury	Brown	Clark	Codington	Day	Deuel	Grant	Hamlin	Marshall	Roberts	Spink
Lost Cropland	$371	$330	$404	$398	$338	$382	$387	$383	$400	$391	$403	$368	$391	$337
New Cropland	$369	$336	$407	$398	$341	$388	$393	$384	$405	$397	$407	$377	$388	$341
Cropland Same	$355	$344	$414	$379	$361	$387	$383	$204	$388	$347	$368	$388	$376	$319
Cropland Lost to Water	$355	$322	$388	$374	$315	$362	$375	$381	$258	$347	$386	$302	$347	$325
Cropland from Water	$347	$328	$393	$392	$322	$386	$373	$367	$399	$383	$399	$379	$397	$320
Cropland 1992	$356	$342	$413	$381	$358	$387	$384	$247	$389	$350	$371	$377	$383	$320
Cropland 2018	$356	$343	$414	$381	$360	$388	$384	$215	$389	$352	$368	$398	$376	$321

2017 Mean Soybean Revenue Per Acre	Study Area	Beadle	Brookings	Kingbury	Brown	Clark	Codington	Day	Deuel	Grant	Hamlin	Marshall	Roberts	Spink
Lost Cropland	$446	$302	$501	$484	$355	$501	$521	$491	$520	$505	$530	$482	$502	$324
New Cropland	$427	$305	$505	$484	$357	$505	$529	$492	$527	$512	$536	$501	$498	$326
Cropland Same	$404	$307	$510	$483	$362	$501	$509	$264	$502	$439	$473	$498	$484	$292
Cropland Lost to Water	$451	$296	$483	$462	$343	$483	$509	$487	$343	$448	$521	$395	$461	$312
Cropland from Water	$386	$303	$492	$480	$335	$505	$509	$472	$524	$500	$528	$491	$511	$320
Cropland 1992	$409	$306	$509	$483	$361	$501	$510	$319	$503	$443	$479	$490	$492	$294
Cropland 2018	$404	$306	$510	$483	$362	$501	$510	$277	$504	$446	$474	$520	$483	$295

2017 Mean Pastureland Revenue Per Acre	Study Area	Beadle	Brookings	Kingbury	Brown	Clark	Codington	Day	Deuel	Grant	Hamlin	Marshall	Roberts	Spink
Lost Cropland	$176	$174	$215	$198	$144	$182	$193	$199	$206	$188	$205	$159	$172	$143
New Cropland	$173	$174	$215	$191	$137	$188	$201	$181	$211	$190	$210	$168	$164	$142
Cropland Same	$178	$174	$210	$179	$148	$187	$205	$151	$211	$195	$210	$162	$177	$155
Cropland Lost to Water	$157	$169	$198	$176	$126	$131	$126	$221	$128	$143	$115	$111	$121	$160
Cropland from Water	$168	$182	$210	$215	$141	$196	$210	$180	$216	$179	$222	$157	$174	$146
Cropland 1992	$177	$174	$211	$181	$148	$187	$204	$162	$211	$195	$209	$160	$175	$155
Cropland 2018	$177	$174	$211	$179	$146	$188	$206	$147	$211	$195	$211	$172	$171	$154

Table 4. Estimated Difference in Revenue, Net Income, and Probability of Being Used Mostly as Cropland, 2008–2017 Period

	Mean Difference in Revenue for a Corn and Soybean Rotation Compared to Pastureland (2008–2017)	Mean Difference in Net Income for a Corn and Soybean Rotation Compared to Pastureland (2008–2017)	Mean Probability of Being Used Mostly as Cropland
Non-Cropland	$66.18	–$17.92	50.18%
Cropland Same	$87.19	–$6.58	91.54%
Non-Cropland to Cropland	$80.09	–$11.92	78.71%
Water to Cropland	$72.06	–$15.80	74.02%

Table 5. Cropland and Non-Cropland Lost to Water Total Assessment Change (Millions of Dollars) for Northeast South Dakota Counties

Total Assessment Change (Millions)	Study Area	Beadle	Brookings	Kingbury	Brown	Clark	Codington	Day	Deuel	Grant	Hamlin	Marshall	Roberts	Spink
Cropland Lost to Water	–$25.70	–$0.50	–$2.00	–$0.90	–$3.50	–$3.50	–$1.30	–$9.20	–$0.20	–$0.60	–$1.00	–$1.20	–$1.30	–$0.60
Non-Cropland Lost to Water	–$45.00	–$0.80	–$2.20	–$0.60	–$4.50	–$10.30	–$12.00	–$2.00	–$1.40	–$1.90	–$5.50	–$0.70	–$0.70	–$2.30

Indiana Corn and Soybean Returns to Storage





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Abstract

On-farm storage is a common merchandising tool. However, evaluation of optimal storage strategies remains incomplete. In this article we provide farm managers a better understanding of the opportunities for earning storage returns and the strategies for doing so that best fit their operations.

Results indicate that maintaining a portfolio of marketing tools, including unhedged and hedged storage, in conjunction with timing strategies is recommended to capture upside potential and spread out risk. In practice, however, every year is different. Farm managers must read storage signals in a given year and adjust their strategy accordingly.

INTRODUCTION

Marketing risk is consistently rated by farm managers as one of the most important risks they face in managing their farm business (Farm Credit Services of America, 2017; Thompson et al., 2019). Farm managers have a myriad of pricing tools and strategies available to them when it comes to when and how they merchandise their grain. A common practice on many farms is to store at least a portion of the production at harvest and deliver it to market later (Farm Credit Services of America, 2017). Over the past decade, on average, 82% of Indiana's corn production and 72% of Indiana's soybean production was in storage on December 1, with the majority located in on-farm storage (USDA, 2019).

Despite the prevalence of storage as a merchandising tool, evaluation of optimal storage strategies remains scant. Instead, storage on many Midwest farms appears to be a product of the availability of on-farm storage, harvest logistics, and convention. Rigorous evaluations of storage decisions and strategies used by farm managers are lacking. In this study, we evaluate average returns and risks of storing corn and soybeans in Indiana. We examine trends in basis, futures prices, and futures carry, which are the drivers of storage returns. Results of this analysis provide farm managers with a better understanding of the opportunities for earning storage returns and the strategies for doing so that best fit their operations.

This work draws on the legacy of seminal research by Working (1949), who first developed the theory addressing the problem of inter-temporal price relationships and their impact on storage returns. In addition, we build on more recent studies that pragmatically address returns to storage, such as Hurt (2017, 2019) and Knorr (2017). Hurt (2017, 2019) evaluated speculative, or unhedged, storage of corn and soybeans at a single central Indiana location over several historical time horizons but did not compare speculative storage to any other merchandising strategies. Knorr (2017) compared multiple merchandising strategies for multiple locations across the Midwest from the 1985–1986 through the 2016–2017 marketing years. However, Knorr's study is limited by the fact that only storage until July was considered and thus does not consider the effectiveness of other storage strategies throughout the storage season.

The objective of the current study is to evaluate the average returns to storage for corn and soybeans in Indiana without imposing the key limitations of previous research with respect to timing and choice of strategy. In doing so, we attempt to address the two primary questions faced by farm managers storing grain:

(i) Merchandising strategy: Should I store corn/soybeans unhedged or hedged?

(ii) Timing: How long should I store corn/soybeans?

It is important to point out that this research does not aim to address optimal merchandising strategy of the crop in general. The focal point of the questions outlined above is limited to the merchandising of post-harvest stored corn and soybeans. Stated another way, once a producer makes the initial decision to store, we assess returns to unhedged or hedged storage and also evaluate how long corn/soybeans should be stored. In addition to answering these two main questions, we also provide insights into several other important aspects of merchandising stored grain. For example, in addition to average returns, we evaluate and discuss the risk-return tradeoff of various storage strategies, along with the tradeoffs related to the timing of futures contract sales on the returns to hedging. All of these aspects have important implications for farm managers seeking to improve their marketing risk management plans, in particular how and when they merchandise stored corn and soybeans.

DATA AND METHODOLOGY

Monthly Indiana state average corn and soybean cash prices are used (USDA, 2019). Data was collected from 1988–1989 to 2017–2018 marketing years. Corresponding futures prices were monthly averages of Chicago Board of Trade daily settlements. Futures prices were collected for each contract month in a given crop-marketing year.

The storage season is defined as starting in October, de facto "harvest," and lasting through September of the following calendar year. Farm managers are assumed to be able to store grain from October through the following September, but not beyond one year. The farm manager's merchandising strategies are limited to storing unhedged or hedged. Unhedged storage involves placing the grain in the bin and taking no position in the futures market until the grain is priced and delivered in the local cash market. This is the simplest, and likely most common, merchandising strategy for stored grain. In this case, the gross return to storage is simply the change in cash price from October to the month when the cash sale is made. Farm managers choosing to store grain unhedged are simultaneously speculating on both futures price and basis, where basis is defined as cash price minus futures price.

The second merchandising strategy evaluated is to hedge grain in storage by selling futures as a temporary substitute for the cash sale that is going to occur later. Recall that cash price equals futures price plus basis. Once the farm manager sells the futures contract, the futures price component of the cash price is established or "locked in." Thus, the farm manager effectively eliminates futures price risk but continues to speculate on basis. This strategy is designed to take advantage of increases in basis during the storage season and relies on the fact that basis risk tends to be significantly lower than futures price risk (Wisner and Hofstrand, 2015). Hence, storage hedging provides the opportunity to earn positive returns to storage in a reduced-risk environment.

We start with a scenario, the basic storage hedge, in which the initial futures hedge is made at harvest in October (sell futures in October), once the grain is in the bin. In this scenario the farm manager is assumed to sell directly into the futures contract closest to the expected cash sale. Farm managers can sell any of the futures contracts available in a given crop-marketing year, and it is assumed that a futures contract could be held up to, but not into, the futures contract's expiration month. For example, for an expected sale of cash corn in May, the farm manager would sell July corn futures in October rather than May futures, since we assume that a May corn futures contract can only be held through the end of April but not into the contract expiration month of May. Once May arrives and the cash sale is made, the farm manager simultaneously buys back the July futures contract, offsetting the original short futures position. The gross return to storage in this scenario equals the change in basis that took place from October to May, when the cash corn sale is made.

However, there are important nuances to the basic storage hedge strategy that should be addressed. Mainly, the timing of the initial futures hedge becomes important because of futures price seasonality (Wisner et al., 1998). For this reason, we provide a brief overview of futures price seasonality, as well as seasonality in price spreads across futures contracts for corn and soybeans. From this, we identify and evaluate a version of the hedged merchandising strategy where grain is hedged prior to harvest by selling new crop futures.

To estimate net returns, carrying charges are subtracted from gross returns. In this analysis, the relevant carrying charges are the marginal costs incurred for carrying the physical commodity for one additional month. Fixed costs are ignored since they will be incurred regardless of the length of storage and merchandising strategy.

The carrying charge is made up of two components: (i) storage cost and (ii) interest, or opportunity, cost on the money invested in the corn or soybean inventory. In this analysis, we assume an on-farm storage cost of $0.01 per bushel per month. While this cost will obviously vary from farm to farm, assigning some cost to on-farm storage is important to account for management, electricity, physical grain losses, etc. The interest, or opportunity, cost on stored corn or soybeans accounts for the fact that cash generated from grain sold at harvest could have been used to pay down debt or reinvested to earn a return. However, by storing grain, these opportunities are foregone and therefore must be assigned to the cost of storing grain. Here we assume an annual percentage rate (APR) of 6%. Again, this value will vary from farm to farm depending on the interest rate faced. The only difference between the per bushel cost of storing corn and soybeans is the interest cost difference between storing relatively lower priced corn versus higher priced soybeans. Costs associated with possible futures margin calls were not considered for the hedged scenario since it's not possible to accurately anticipate futures margin calls.

RESULTS AND DISCUSSION

Corn Futures Seasonality and Futures Carry

The basic storage hedge strategy is implemented by selling futures at harvest in October when grain is placed in storage. However, previous research has shown that selling futures at harvest tends to lock in seasonally low futures prices (Wisner et al., 1998). Therefore, we also evaluate how relaxing the assumption of a routine October futures sale affects returns to the hedging strategy.

To do so, we first developed a 30-year (1988–1989 to 2017–2018 marketing years) seasonal index of new crop December corn futures prices from the first week of January through the end of November, prior to December expiration (Figure 1). The seasonal index has a reference value of 100 for the first week of January. Subsequent values above or below 100 indicate that prices that week tended to be seasonally higher or lower than during the first week of January, respectively. For example, a value of approximately 104 for the third week of June indicates that new crop December corn futures prices the first week of June were, on average, 4% higher than during the first week of January.

The chart reveals that, similar to Wisner et al. (1998), new crop December corn futures were seasonally high during the late spring and early summer months when uncertainty about the condition of the new crop reaches its peak. Conversely, new crop corn futures tended to reach their seasonal lows during the fall. Thus, initiating the hedge earlier by selling new crop corn futures during the summer prior to harvest has the potential to improve returns compared to the basic storage hedge where the initial futures sale takes place in October.

However, it's important to also consider the impact of the timing of the futures sale on futures carry. That is, how does the timing of the futures sale impact the spread between futures prices of the various contracts? In the basic storage hedge strategy, it's assumed that the farm manager sells directly into the deferred futures contract closest to the expected cash sale date, effectively locking in futures carry that existed on the day the futures contract was sold. But changing the timing of the futures sale may change the futures carry captured when selling the deferred contract, depending on the dynamics of futures price spreads.

For simplicity, consider the spread between new crop December and July corn futures. Figure 1 also illustrates the average difference between new crop December corn futures price and the subsequent July corn futures price for each week from the first week of January to the last week of November. For clarity, during the first week of January 2017, this would be the difference between July 2018 corn futures and December 2017 corn futures.

As you can see, the spread between July and December futures widens as the December corn futures contract approaches expiration. The widening of the spread means the carrying charge provided by the futures market was increasing, providing a larger premium for storing grain from December to July. Hence, the basic storage hedge, where the farm manager initiated the hedge by selling futures in October, generally locked in the futures carry near its peak for the year. However, it also locked in futures prices at their seasonal lows. Conversely, selling futures earlier in the year prior to harvest makes it possible to lock in seasonally high futures prices but forgoes the opportunity to lock in futures carry when it tends to reach its seasonal peak. So, what can farm managers do to capture both seasonally high futures prices and maximize futures carry?

One alternative would be to use a hedge and roll strategy. That is, the farm manager would place the initial futures hedge in the new crop December corn futures contract during the summer months prior to harvest, capturing, on average, seasonally higher futures prices without locking in futures carry. Then once futures carry widens, typically closer to expiration of the December contract, the farm manager would roll the December futures hedge forward. This involves simultaneously buying back the original December futures contract and selling one of the deferred contracts within the same marketing year. The difference in the price between the two contracts when the roll occurs is the additional futures carry captured by the hedger. Finally, when the cash sale takes place, the farm manager buys back the short futures position.

While this strategy offers an increased layer of complexity, mainly through the additional futures transactions and a heightened need to monitor futures market positions, it offers the farm manager the opportunity to capture seasonally strong futures prices and futures carry, potentially making storage much more profitable.

Returns to On-Farm Corn Storage

Average cumulative net returns for on-farm corn storage following the (1) unhedged storage; (2) basic storage hedge; and (3) hedge and roll strategies are reported by month in Figure 2. These are 30-year (1988–1989 to 2017–2018 marketing years) averages of monthly returns and are net of assumed on-farm storage costs ($0.01/bushel/month) and interest costs (6% APR). Average net returns to storage for the unhedged strategy increased steadily from harvest through spring, reaching a peak in April and May of approximately $0.30/bushel. After May, average returns to storage for the unhedged strategy declined precipitously, largely due to declining cash prices and accumulating storage and interest costs. This pattern is very similar to results presented by Hurt (2017, 2019) for the returns to unhedged on-farm corn storage at a single central Indiana location.

Similarly, average net returns to storage for the basic storage hedge strategy, where the initial hedge is placed in October, increased steadily from harvest through spring, reaching a peak of around $0.20/bushel between May and August. This result is consistent with Knorr's (2017) finding that average net returns to storing hedged corn on-farm for July delivery in central Indiana was $0.14 to $0.21/bushel, depending on the historical time frame evaluated.

Finally, average net returns to the hedge and roll strategy started at $0.22/bushel in October given that corn futures prices in June prior to harvest were, on average, higher than corn futures prices in October and subsequently peaked at over $0.40/bushel between May and August. Given that the seasonal difference in futures prices is the only practical difference between the hedge and roll strategy and the basic storage hedge strategy as defined here, the line representing average net returns to the hedge and roll strategy runs parallel to and is $0.22/bushel higher than the basic storage hedge strategy throughout the storage season.

A comparison of the three strategies' results reveals that, on average, the hedge and roll strategy provided the highest net returns throughout the entire storage season. It is also worth noting that the unhedged strategy yielded higher average net returns than the basic storage hedge strategy through most of the storage season. The one exception occurred late in the storage season, when returns to unhedged storage declined. The implication is that farm managers planning to store corn into the summer months should strongly consider using one of the two hedged strategies.

Although looking at the long-term averages in Figure 2 is a useful exercise for understanding expected seasonal patterns in storage returns, there is a lot of information underlying those averages since each data point on the chart is composed of the average of 30 years of results. As pointed out by Hurt (2019), one unusual year can have a large influence on average returns. Therefore, examining the distribution of returns over time for each strategy helps decision-makers evaluate the risk-return tradeoff of these merchandising strategies. To do so, we select a single month, May, to evaluate the returns to storage for each strategy over each of the past 30 years. May was selected given that it generally provided the highest average net returns for all three strategies. Therefore, results in Figure 3 represent the annual net returns to storing corn on-farm from October to May for each of the past 30 years.

Notice that returns to unhedged storage for corn tended to be more volatile—higher highs and lower lows—than the basic storage hedge strategy (sell July futures in October). The upside potential for storing corn unhedged was largely captured in three years when net returns were greater than $1.50/bushel (1995, 2007, and 2010). Each of these three years was characterized by a large rally in futures prices between October and May. Omitting these three years, the average net return to storing corn on-farm unhedged from October until May dropped from $0.30/bushel to just $0.13/bushel. In addition, the unhedged strategy also exposed the farm manager to more downside risk than the basic storage hedge. Notice that net returns to storage for the unhedged strategy were negative in seven of the past 30 years and averaged –$0.22/bushel, whereas net returns to the basic storage hedge were negative in just two of the past 30 years and averaged –$0.03/bushel.

Annual net returns to the hedge and roll strategy were positive in 24 of the past 30 years. However, it is important to note the large downside risk experienced in 2010 and 2012. In these years, futures prices rallied after the initial hedge was placed in June, resulting in lower sale prices than what would have been received at harvest. Exacerbating this loss, 2012 was a short crop year, and the futures market inverted, meaning at harvest the nearby contract was trading above the deferred contracts. As a result, rolling the hedge in the inverted market added to the losses in 2012. In practice, no farm manager would roll a hedge in an inverted futures market. However, for illustrative purposes we followed the strategy as described in every year. This is a good example of why storage strategies should be adapted for each year based on storage signals provided by the futures and cash markets in a particular year and not followed blindly.

Finally, it is instructive to think about which strategy produced the highest returns most frequently. Among the three strategies evaluated, hedge and roll generated the highest returns to on-farm corn storage until May in 17 of the past 30 years, seven of the past 10 years, and two of the past three years. Thus, the hedge and roll strategy not only provided the highest net return on average for corn stored on-farm until May but also produced the highest net returns most frequently among the three strategies examined here. It is also worth noting that the basic storage hedge strategy produced higher net returns than the unhedged strategy in 17 of the past 30 years, seven of the past 10 years, and two of the past three years. Hence, although the unhedged strategy produced higher average returns than the basic storage hedge over the past 30 years, this average was skewed by just a few good years. In contrast, net returns to the basic storage hedge strategy provided more modest but also more consistent returns.

Soybean Futures Seasonality and Futures Carry

It is important to note that soybeans and corn do not follow the same seasonal patterns for futures prices, futures carry, or basis—and it's important to understand the differences. The new crop November soybean futures price index and the average futures price spread between new crop July soybean futures minus new crop November soybeans futures are reported in Figure 4. Again, similar to Wisner et al. (1998), new crop November soybean futures prices were seasonally high during the summer months and seasonally low around harvest in the fall. The timing of the futures sale also affects the futures price spread the hedger is locking in, with the average premium of new crop July soybean futures over November soybean futures being smallest during the summer months and largest around harvest.

So again, farm managers face a dilemma regarding how to both capture seasonally high futures prices and maximize futures carry. The hedge and roll strategy provides farm managers the flexibility to capture seasonally high futures price opportunities by selling into the new crop November soybean futures contract prior to harvest during the summer months, when prices are seasonally strong, without locking in futures carry that is seasonally weak. As futures carry widens into the fall, near the November futures contract's expiration, the farm manager would roll the hedge forward, locking in the seasonally wide futures carry.

Returns to On-Farm Soybean Storage

Average cumulative net returns to on-farm storage for soybeans for each of the three strategies evaluated (unhedged, basic storage hedge, and hedge and roll) are reported by month in Figure 5. Similar to corn, average net returns to storage for the unhedged strategy increased steadily from harvest through spring, reaching a peak between May and July of nearly $0.70/bushel. After July, average returns to storage for unhedged soybeans declined, again due to declining cash prices and accumulating storage and interest costs. This pattern is very similar to results presented by Hurt (2017, 2019) for the returns to unhedged soybean storage at a single central Indiana location.

Average net returns to storage for the basic storage hedge strategy (sell futures in October) increased from harvest through the end of the calendar year, reaching a peak of around $0.10/bushel. From January to May the average net returns to the basic storage hedge stalled out or even declined. This period of time coincides with the South American soybean harvest, resulting in relatively flat basis patterns. Given that the gross returns to the hedged strategy are driven by appreciation in basis, a period of flat basis and accumulating storage and interest costs results in deteriorating net returns to storage. Nonetheless, our results suggest slightly better performance of the basic storage hedge strategy than Knorr (2017), who reported average net returns of –$0.01 to –$0.04/bushel for hedged soybeans stored on-farm until July in central Indiana.

Finally, average net returns to the hedge and roll strategy start at $0.40/bushel in October given that soybean futures prices in July prior to harvest were, on average, higher than soybean futures prices in October. Again, the opportunity to capture the seasonal strength in soybean futures prices afforded by the hedge and roll strategy is the only practical difference between the hedge and roll strategy and the basic storage hedge strategy as defined here, resulting in average net returns to the hedge and roll strategy and the basic storage hedge strategy running parallel throughout the storage season. Average net returns to the hedge and roll strategy increased gradually from harvest through the end of the calendar year, reaching a peak of around $0.53/bushel in December.

Comparing results from the three strategies, the hedge and roll strategy produced the highest average returns early in the storage season given the instant bump in returns from locking in seasonally higher futures prices. However, by March average net returns to the unhedged strategy actually surpassed the hedge and roll strategy until August, when returns to the hedge and roll strategy were again higher than the unhedged strategy due to sharp declines in unhedged returns.

Again, it is useful to consider the distribution of returns underlying these averages. The net returns to storing soybeans on-farm from October to May for each of the past 30 years are reported in Figure 6. Returns to unhedged storage for soybeans were again more volatile than returns for the basic storage hedge strategy. However, the upside potential for storing soybeans on-farm appears to outweigh the downside risk. For example, the net returns to storing unhedged soybeans on-farm until May was greater than $0.50/bushel in 14 of the past 30 years, which is remarkable. On the downside, storing unhedged soybeans on-farm until May only generated negative net returns in nine of the past 30 years, with losses in those nine years averaging –$0.41/bushel. For comparison, net returns to the basic storage hedge were negative in 10 of the past 30 years, with losses in those 10 years averaging –$0.28/bushel.

Average net returns to the hedge and roll strategy were positive in 21 of the past 30 years. However, similar to corn, the hedge and roll strategy also produced large downside risk in a few years, such as in 2003. This large negative return resulted from a rally in futures prices following the initial hedge in July. In addition, 2003 was a short production year for soybeans, resulting in an inverted futures market. Thus, rolling the hedge in October resulted in a loss of an additional $0.60/bushel relative to having just bought back the original short November futures position. So again, in practice, most farm managers would not have rolled the hedge in the fall of 2003, thereby mitigating the loss of more than $1.50/bushel shown in Figure 6.

Finally, it is instructive to think about which strategy produced the highest returns most frequently. The unhedged strategy generated the highest returns to on-farm soybean storage when stored until May in 14 of the past 30 years, five of the past 10 years, and two of the past three years (through the 2017 crop year). Therefore, while the hedge and roll strategy greatly improved average returns and the frequency of positive returns relative to the basic storage hedge strategy, the strong performance of unhedged on-farm soybean storage is still evident.

CONCLUSIONS

The objective of this research was to evaluate the historic returns to storage for corn and soybeans in Indiana to identify storage strategies farm managers could use to improve crop storage returns. Results indicate that storing corn and soybeans on-farm in Indiana can be a profitable merchandising strategy. Furthermore, results suggest that managers should consider employing a portfolio of marketing strategies since it's not possible to predict with certainty which individual strategy will generate the highest returns in a given year. Using a portfolio of marketing tools, including unhedged storage, simple storage hedges, and rolling hedges is recommended to capture upside potential and spread out risk.

The simple—and most common—strategy of storing corn and soybeans unhedged into the spring, on average, generated positive returns for both crops. However, this strategy carries the most risk, exposing managers to both futures price and basis risk. Still, returns for this strategy were high enough, especially for soybeans, that using this strategy as one component in a portfolio of marketing strategies makes sense for managers willing to take on both futures price and basis risk.

Basic storage hedges, in which the farm manager places a hedge in a deferred futures contract when grain is placed in storage at harvest time, can reduce risk by locking in the futures price component of cash price, as well as provide an opportunity to improve returns by capturing basis improvement during the storage season. Over the 30 years examined in this study, the simple storage hedge generated a positive average return for both commodities, but it was a far more effective strategy for corn than for soybeans. In particular, the basic soybean storage hedge did not improve returns for soybeans stored into the early winter and spring months.

For managers willing to go beyond the simple storage hedge to improve returns, the rolling a hedge forward strategy can improve returns and is worthy of consideration. The rolling hedge strategy takes advantage of the seasonality in new crop corn and soybean futures by initiating the sale in new crop December corn or new crop November soybean futures in late spring or early summer, when futures prices are seasonally strong. In the fall, at or shortly after harvest, the manager rolls the hedge forward to a deferred corn or soybean futures contract, which allows them to capture the seasonal strength in futures market carry and, combined with basis improvement, generates a positive return to storage. On average, this strategy provided the highest storage returns for corn and the second highest storage returns for soybeans, albeit at much lower risk than the highest average soybean storage return strategy, which was to simply store unpriced.

It is important to point out that these results are based on historical data. While historical data is useful for helping form expectations about the future, it is not a guarantee of what will actually happen in the future. Farm managers should read storage signals in a given crop-marketing year and adjust crop-marketing plans accordingly. As seen in our analysis, naively following one or more of these strategies can actually reduce returns compared to selling at harvest. Most simply, given that the focus of this study is on returns to storage, the best advice we can give is to avoid storing in years that history says are likely to provide negative returns to storage. Negative returns to storage are most likely to occur in short crop production years when basis at harvest is relatively strong and futures carry is unusually narrow or possibly inverted with deferred futures contracts within the marketing year trading at a discount to nearby harvest time futures. Both of these market features are strong market signals that there is little likelihood of earning positive storage returns.

Finally, while the empirical application of this paper focuses on a case study of Indiana, the strategies described and implications of our results are widely relevant for farm managers throughout the Midwest and beyond. The information regarding corn and soybean futures is universal. Therefore, evaluating the performance of these strategies for other locations would only require knowledge of local basis patterns. Robustness of the results presented here has been investigated for surrounding states (Illinois, Michigan, and Ohio), and qualitative patterns in returns are generally consistent. However, it is important to note differences in quantitative levels of returns given differences in local basis patterns. For those interested in assessing these results for their local market regions, local basis information is available from several sources around the country; we are aware of the following sources:

- **Purdue Center for Commercial Agriculture Crop Basis Tool (2019)**
  States: Indiana, Illinois, Michigan, and Ohio
  Crops: Corn and soybeans
  Link: https://ag.purdue.edu/cropbudget/multi.php

- **farmdoc Corn & Soybean Basis Tool (2019)**
  States: Illinois
  Crops: Corn and soybeans
  Link: https://farmdoc.illinois.edu/fast-tools/corn-soybean-basis-tool

- **Iowa State University Corn and Soybean Price Basis (2019a, 2019b)**
  States: Iowa
  Crops: Corn and soybeans
  Link (corn): https://www.extension.iastate.edu/agdm/crops/pdf/a2-41.pdf
  Link (soybean): https://www.extension.iastate.edu/agdm/crops/pdf/a2-42.pdf

- **Kansas State University Interactive Crop Basis Tool (2019)**
  States: Kansas, Missouri, Nebraska, Oklahoma, and Texas
  Crops: Corn, soybeans, and wheat
  Link: https://www.agmanager.info/grain-marketing/interactive-crop-basis-tool

- **Montana State University Wheat Basis & Price Forecasting Tool (2019)**
  States: Montana and Washington
  Crops: Wheat
  Link: http://wheatbasis.montana.edu

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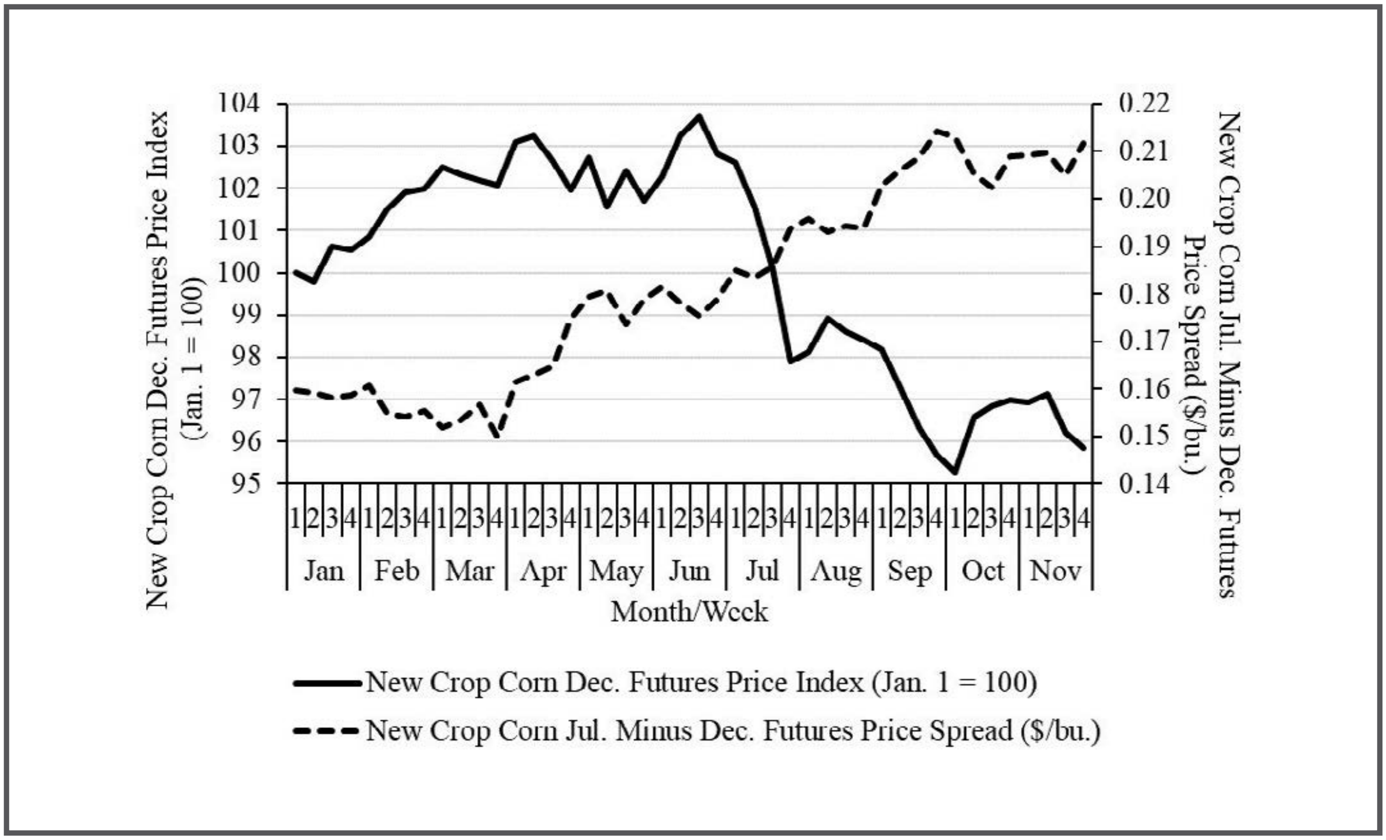

Figure 1. 30-Year (1988–1989 to 2017–2018 Crop-Marketing Years) Average New Crop Corn December Futures Price Index and New Crop Corn July Minus December Futures Price Spread by Week

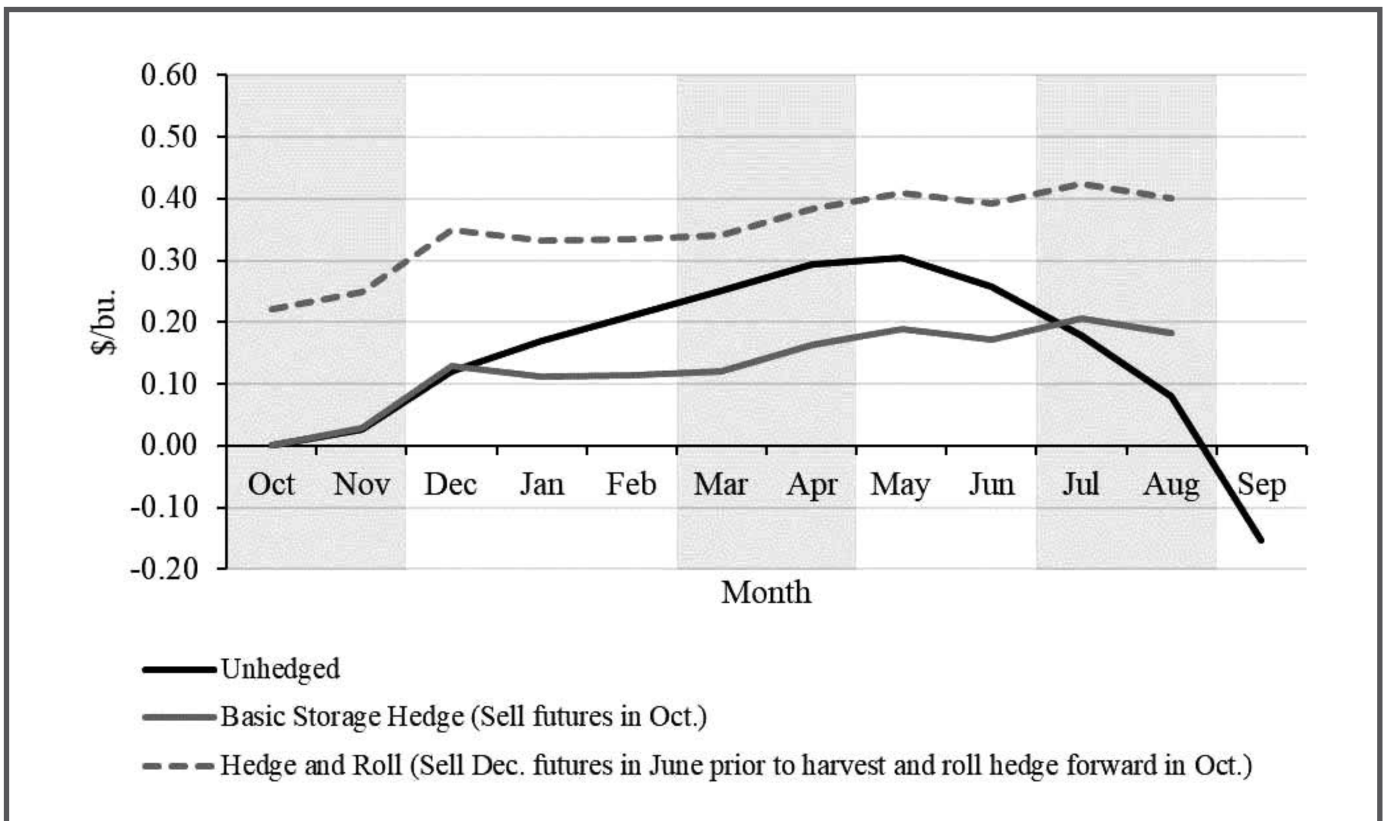

Figure 2. 30-Year (1988–1989 to 2017–2018 Crop-Marketing Years) Indiana Average Net Returns to Storage for Corn by Month

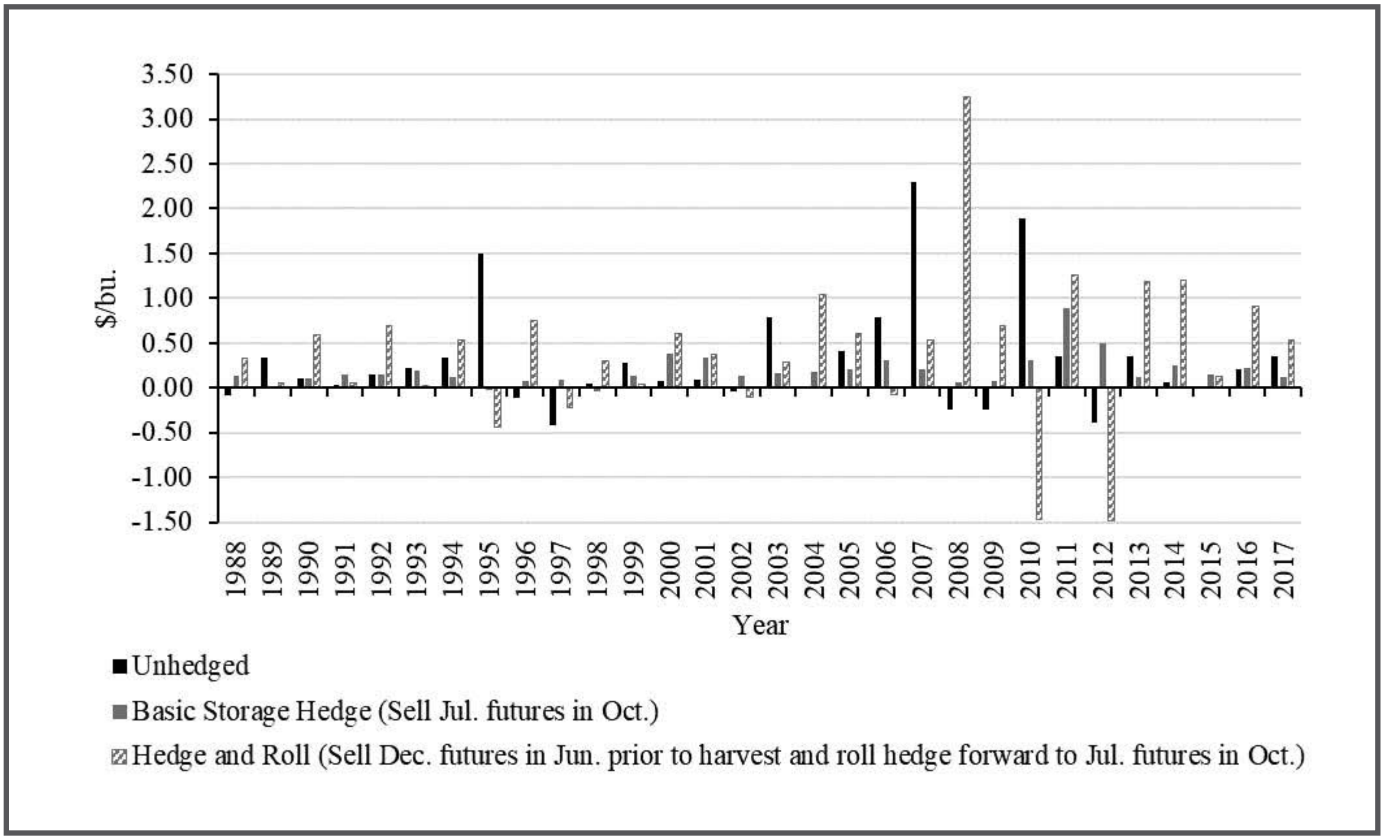

Figure 3. Annual Indiana Net Returns to Storage until May for Corn, 1988–1989 to 2017–2018 Crop-Marketing Years

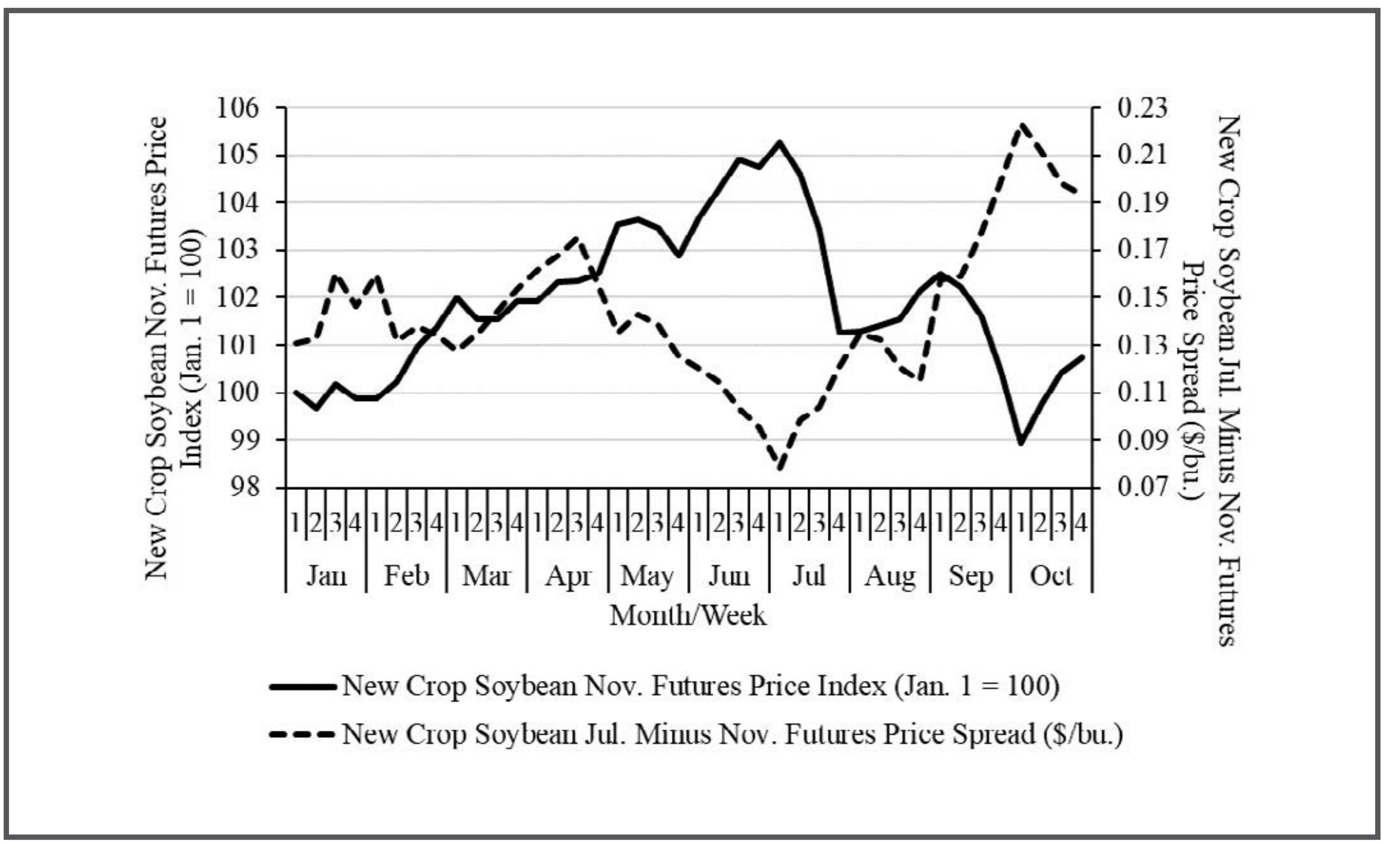

Figure 4. 30-Year (1988–1989 to 2017–2018 Crop-Marketing Years) Average New Crop Soybean November Futures Price Index and New Crop Soybean July Minus November Futures Price Spread by Week

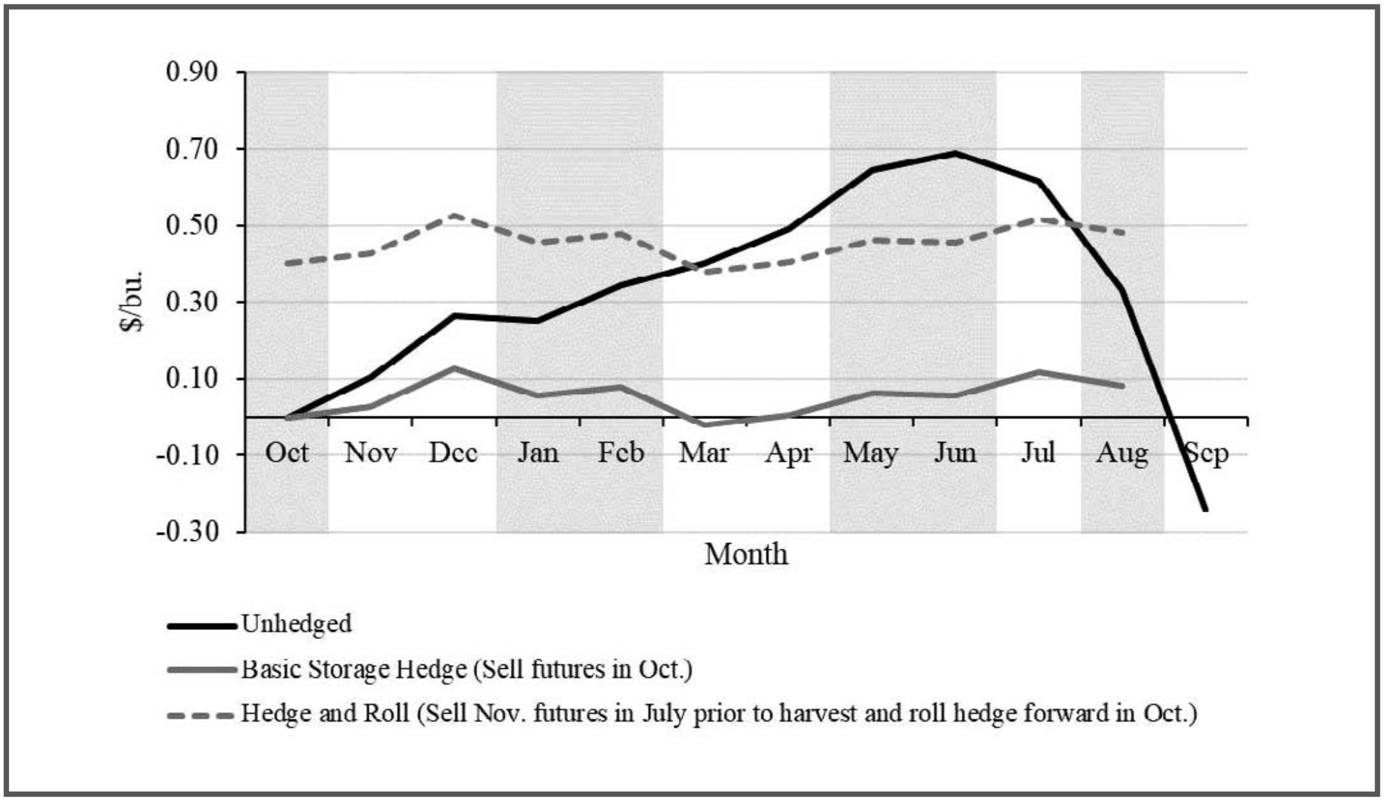

Figure 5. 30-Year (1988–1989 to 2017–2018 Crop-Marketing Years) Indiana Average Net Returns to Storage for Soybeans by Month

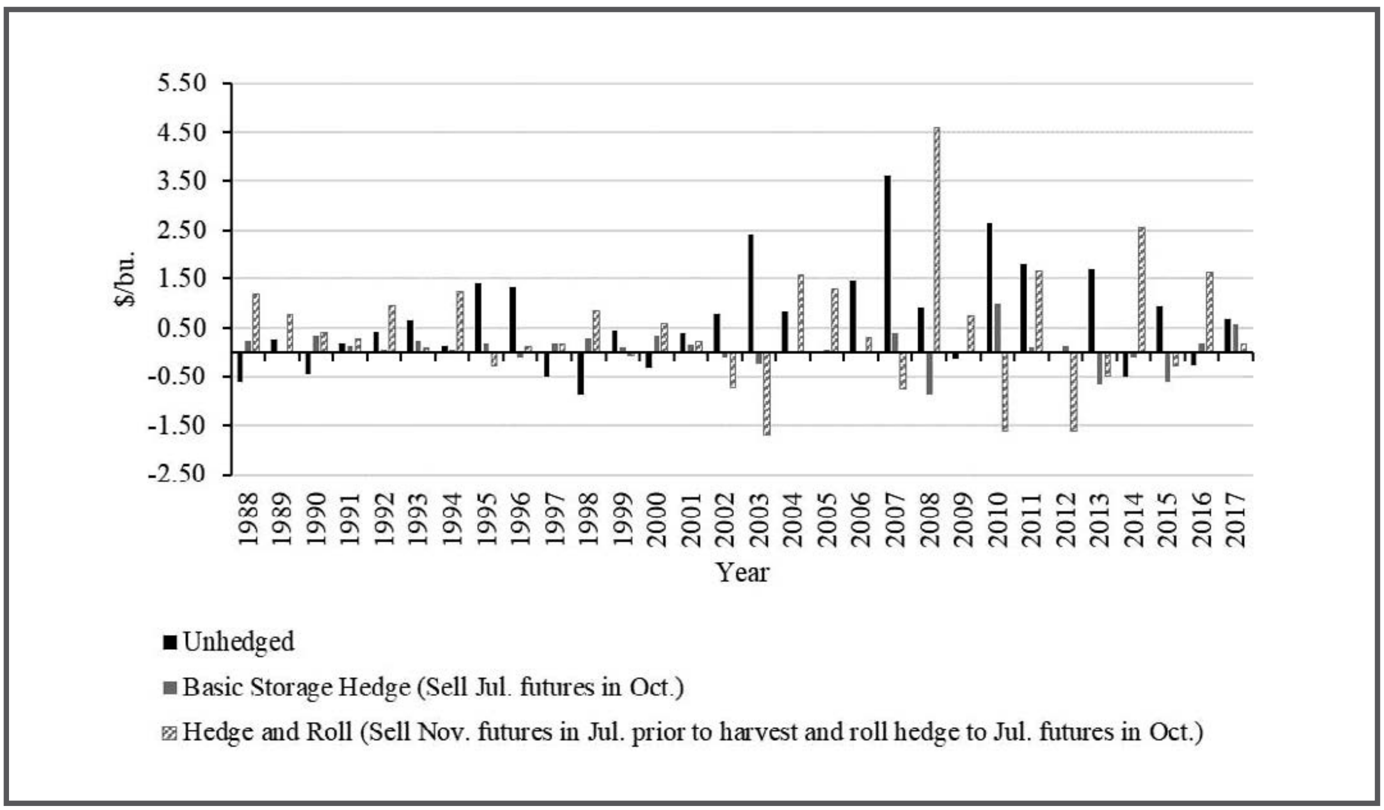

Figure 6. Annual Indiana Net Returns to Storage until May for Soybeans, 1988–1989 to 2017–2018 Crop-Marketing Years

Green Acres: A Study of Cropland Values in Mississippi




By Evan Gregory, Xiaofei Li, Bryon J. Parman, and Keith H. Coble

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Abstract

Using parcel level and sub-parcel level data from Mississippi cropland sales, estimates of the value of cropland and the respective characteristics are rendered. Such a study has not been conducted in the state of Mississippi. Hedonic models as well as a spatial error model is used. The results indicate that physical improvements, soil characteristics, and regional characteristics have a significant impact on the value of cropland.

INTRODUCTION

Farm real estate has been estimated to comprise around 83% of the value of farm assets in 2019 (Economic Research Service, 2019). Therefore, any change in the value of farm real estate will have a substantial impact on the wealth of farm owners. Since farm real estate holds great value to the farm owner, it is imperative that those who buy and sell cropland have a good understanding of the factors that can influence the value of cropland.

Farm real estate values have increased dramatically since the late 1960s. This trend can be seen in Figure 1, created by data collected from the Economic Research Service (2018). Since 2014, farmland values have decreased nationally after a period of appreciation that had been occurring since the 1980s (Economic Research Service, 2018). Currently, estimates show that national cropland values decreased by around 1% between 2017–2018 when adjusted for inflation. In the southeastern region, cropland values decreased by approximately 2% during the same time period. The differences in the amount of change in land values indicate that changes in cropland values may be different depending on where the land is located, and even nearby states may face different trends. Therefore, land owners can benefit greatly by knowing how differing amenities and characteristics influence the value of cropland in the particular state or region in which they are located.

Many existing studies use county-level and parcel-level data to estimate the effect of amenities and characteristics on the value of cropland, but there has been no such study in the state of Mississippi. Dunford, Marti, and Mittelhammer (1985) concluded that soil quality, parcel size, and location can impact land values significantly. Ervin and Mill (1985) found that an increase in the slope of the land and erosion decreased farmland values. Also, as the productivity index of the soils increased, farmland values increased. Palmquist and Danielson (1989) found that erosion control and drainage affected farmland values. Maddison (2000); Drescher, Henderson, and McNamara (2001); and Bastian et al. (2002) came to contradictory conclusions over the effect that parcel size had on farmland values.

We conduct a hedonic regression analysis on the value of various cropland characteristics at a parcel and sub-parcel level. The unique nature of our dataset allows us to estimate the value of various improvements made to the land, in particular precision leveling, average slope, the available water storage of soil, and the average depth to the nearest wet soil layer of each parcel. In addition to the hedonic regressions, a spatial error model is used to account for spatial autocorrelation that is present in the dataset.

The results of this study indicate that soil quality and irrigation capabilities greatly affect the market value of cropland. Buyers are willing to pay a premium for land that is precision leveled. In addition, the results show that slope and the depth to the nearest wet soil layer also have a significant impact on the value of cropland. Regional and urban influences, as well as county level per capita income, are observed to significantly affect cropland values.

It is important to note that this study is to our knowledge the first that uses "sub-parcel" level data in its analysis. Also, to our knowledge this is the first study that analyzes the effect of the depth to the nearest wet soil layer on the market value of cropland. The importance of this variable is in the fact that it is indicative of the soil's ability to drain. This study also surveys the use of different types of data and different regression models. The significance of using multiple regression models and datasets is that the study illustrates the difference in regression estimates across the models and datasets, which can help to further discussion as to the necessity of more complex regression models and datasets in certain situations.

DATA

Data consists of a collection of 345 land sales in the state of Mississippi between the years of 2015–2017 that had at least one acre of cropland in the parcel. The sales include information on the location, size, and various attributes and characteristics of each land sale. Arm's length transactions were able to be identified and used from the dataset, making it possible to assume that price data represented the full market value of land sold.

There are seven cropland types in this dataset, which are defined in Table 1. The definitions for each land type are acquired from the bank in which the data was sourced. The different cropland types distinguish between irrigation capabilities, precision leveling, and other improvements made to the cropland. The land classes are also differentiated on the basis of the crops that they are best suited to producing. Being suited for producing demanding crops such as cotton and corn in comparison to less demanding grain crops such as soybeans allows us to assume that cropland types that are "best suited to cotton or corn" have higher quality soils than other land types. The data also gives "sub-parcel" information on the type of land in each parcel and the amount of each type of land. Summary statistics for the sub-parcel cropland prices can be seen in Table 2. Location of the sales can be seen in Figure 2.

ArcGIS and R were used to obtain the shape files of each land parcel from the original dataset. The shape files were used for the analysis of location characteristics, as well as to overlay soil information over each land parcel. Soil information was acquired through the Soil Survey Geographic Database (SSURGO) that has been compiled by the National Cooperative Soil Survey. Information about soil type, slope, drainage capabilities, and other characteristics is included for every county in the state of Mississippi in the SSURGO dataset. The information is then isolated for each land parcel in the dataset and included in the analysis of cropland values.

Soil Characteristics

Three soil variables will be used in the models, the first of which is the available water storage of the soil up to a depth of 25 cm. More simply, it is the volume of water that the soil can store and that is available to plants. It is common knowledge that plants need water to survive and grow, but the soil's ability to store water for plant use is a property that is beneficial to growers, especially during dry weather conditions. The next soil variable used is slope. For this, we use the weighted average slope gradient of each land parcel. The slope gradient is expressed as a percent. Ervin and Mill (1985) estimated that a 1% increase in slope resulted in a $21.99 decrease in the price per acre of farmland in Page County, Iowa. As the slope gradient increases, the potential for soil erosion can increase, as well as it being increasingly difficult to bring in planting and harvesting equipment into the field. Studies such as Palmquist and Danielson (1989) conclude that potential erosivity, which is influenced by slope, negatively affects farmland values. Therefore, we expect that increasing slope will decrease cropland values.

The next variable, which will be denoted as "wet-depth," is the average shallowest depth to the first wet soil layer at any time of the year. The depth to the first wet soil layer is expressed in centimeters. The reasoning for using the wet-depth variable is that it is indicative of the soil's ability to drain, whether through the structure of the soil or some other factor that affects soil drainage. Much of the sales data used is from the Delta region of Mississippi, which is prone to flooding because of low-lying and relatively flat land. Wet soils can prevent crops from being planted and harvested, which can have devastating effects on the revenue accrued through crop production.

Although to our knowledge no such study has used a similar wet-depth variable, Palmquist and Danielson (1989) indicate that the capability of land being able to drain is a relevant and significant factor in farmland values.

Urban Influence

A GIS shape file that contains information on the location and demographic characteristics of towns and "population clusters" in the state of Mississippi was acquired from the Mississippi Geospatial Clearinghouse. The shape file of the towns and population clusters overlaid on a Mississippi state map can be seen in Figure 2. Population clusters may include towns and nearby areas that have a high population. For example, population clusters include the area surrounding Jackson, Mississippi, and areas that are near Memphis, Tennessee. The shape file contains the population of each town and population cluster so we are able to isolate the areas that have a high population, so we can analyze the effect of those areas on the price of nearby cropland.

We also consider the effect that urban areas may have on cropland values near these areas, which are said to be on the "urban fringe." We calculate the additional value of cropland that is within 10 miles of the border of each urban area when compared to rural cropland. A 10-mile "buffer" is constructed in R, land parcels are overlaid onto the buffers, and every land parcel that intersects the buffers is deemed to be an urban cropland sale.

METHODS

Hedonic Models

The hedonic model assumes that goods are a bundle of heterogeneous characteristics. A change in the characteristics will be met with a change in the willingness to pay for that particular good by the consumer (Rosen, 1974). Understanding that price can be a function of individual attributes, some have developed a functional form that will estimate the impact of attributes on land values (Chicoine, 1981; Ervin and Mill, 1985). The function is denoted as

$$P = \alpha + \sum_{i=1}^{n} \beta_i Z_i + \varepsilon \qquad (1)$$

where α is the intercept, Z_i represents the variables that denote land attributes, β_i represents the coefficient associated with each attribute, and ε is the error term. This function estimates the value of individual characteristics in each land parcel.

Due to the uniqueness of our dataset, we are able to use a parcel level hedonic regression and a sub-parcel level hedonic regression. Since the location of each sub-parcel land type within each parcel is unknown, we are unable to acquire and use soil data from SSURGO in the sub-parcel level hedonic regression. Also, by acquiring soil characteristics at the parcel level, it is only appropriate to use the weighted price of cropland for the entire parcel as the dependent variable in our parcel level regressions. Since we assume that the weighted price of cropland will be skewed toward the dominant cropland type, we include a dummy variable that captures the effect of each dominant cropland type. By using this dummy variable, we believe we can measure the additional value that the individual cropland types may add to the weighted price of cropland within the parcel.

The sub-parcel level regression allows for the estimation of the value of the individual cropland types. Since the different cropland types are indicative of different characteristics, such as precision leveling, furrow irrigation, and pivot irrigation, the additional value of these characteristics can be estimated. A list of variables and the coinciding definitions for the parcel level and sub-parcel level hedonic regression can be seen in Table 1.

Heteroscedasticity and Autocorrelation

A Breusch-Pagan test was conducted on the hedonic model to detect heteroscedasticity, which resulted in rejecting the hypothesis that the model was homoscedastic. Along with the issue of heteroscedasticity, a Durbin-Watson test was conducted to test for the presence of autocorrelation. The null hypothesis of no autocorrelation was rejected after the test was conducted. Since heteroscedasticity and autocorrelation were detected in the hedonic model, the issue was corrected by using heteroscedasticity and autocorrelation robust standard errors (Newey and West, 1987). A test for multicollinearity in the hedonic regression models was conducted by estimating the variance inflation factor for the models, but results indicated that multicollinearity was not an issue.

Spatial Autocorrelation

Spatial autocorrelation is an econometric issue that arises in geographical cross-sectional data (Hardie, Narayan, and Gardner, 2001) in which nearby and distant things are related. For example, the value of agricultural lands that share similar soils but are not within the same parcel can be correlated. Ignoring spatial dependence can result in inefficient coefficient estimates, as well as inaccurate standard errors (Huang et al., 2006).

Cropland in the state of Mississippi is heavily concentrated in the Delta and Black Prairie regions, so some level of positive spatial correlation will likely be present. To test for spatial autocorrelation, Moran's I test was used and indicated that positive spatial correlation was present in the dataset. The results for Moran's I test can be seen in Table 3.

Spatial Error Model

Since spatial autocorrelation exists, the spatial error model is used to estimate the value of the same variables used in the parcel level hedonic model.

The error term of the model is now

$$\varepsilon_i = \lambda \mathbf{W} \varepsilon_i + u_i \qquad (2)$$

where λ is the autoregressive parameter, $\mathbf{W}$ is a spatial weight matrix, and u_i is the independently distributed error.

The spatial weight matrix can be constructed in a variety of ways, but a distance decay (inverse distance) pattern is incorporated since it is assumed that correlation between land parcels will decrease as the distance between land parcels increases. $\mathbf{W}$ is an $N \times N$ matrix in which each "neighbor" of a land parcel receives a non-zero weight. However, it should be understood that for this study every parcel in the dataset within 50 miles of a parcel will be considered to be a neighbor of the parcel. A cutoff point of 50 miles is used to account for within-county correlations; land parcels beyond this distance exhibit little influence on the land parcel of interest.

Results

Several functional forms are estimated, and for all parcel level models the reference category for the dominant cropland type is Cropland 1 (non-irrigated soils; best suited to cotton or corn). The year 2015 is the reference category for the dummy variables corresponding to the year in which each land parcel was sold. The dependent variable for the parcel level hedonic regression and spatial error regression is the weighted average price of cropland in each parcel. For the sub-parcel level hedonic regression, the price per acre of each cropland type is the dependent variable. For simplicity, we present the results as a comparison of all three models. The complete results can be seen in Table 4. For the spatial error model, the estimate for λ, the autoregressive parameter, is statistically significant with an estimate of 0.74. The estimate indicates strong correlation between the error terms in the model and validates our use of the spatial error model.

The results for the differing cropland types are of great value, as we can estimate the value of the differing characteristics of each land type. For example, Irrigated Cropland 1 is precision leveled, flood irrigated land; Irrigated Cropland 2 is furrow irrigated but is not precision leveled. The parcel level models estimate that if the dominant land type is Irrigated Cropland 1, then the average weighted price of cropland in the parcel is worth approximately $131 to $384 more than if the dominant cropland type is Irrigated Cropland 2. The results indicate that land buyers are willing to pay a premium for precision leveled, flood irrigated land when compared to unleveled, furrow irrigated land. Also, the estimates indicate that land buyers generally value all furrow irrigated land types more than non-irrigated land, which was expected.

The spatial error model estimates that a 1-cm increase in the average annual depth to the nearest wet soil layer results in an $8.31 increase in the weighted price per acre of cropland. For the parcel level hedonic model, that same estimate is $8.38. The findings for the wet-depth variable are important because the results indicate that the general wetness of the soils and the soil's ability to drain do influence a parcel's market value.

The spatial error model estimates that cropland within 10 miles of the border of an urban area is around $542 dollars more per acre than land that is not near urban areas. We expected that land prices near urban areas would be significantly different than rural land prices in all models. However, it is an important finding that before we had corrected for heteroscedasticity and autocorrelation, the urban dummy variable was statistically significant for both hedonic regressions. Croplands in the Delta region are estimated to be worth more than $643 per acre than non-delta cropland in the parcel level hedonic model. The sub-parcel hedonic model renders an estimate of over $1,108 per acre premium for delta cropland. The spatial error model results are statistically significant, rendering delta cropland to be worth approximately $353 more than non-delta cropland. Since we are accounting for many factors that make delta soils more desirable and other factors that influence productivity, the variable is most likely capturing unknown variables such as better access to markets.

All models give a positive and statistically significant estimate for the acreage variable. A one-acre increase in the amount of cropland is estimated to increase the weighted average of cropland price anywhere from $0.39 to $0.45 per acre according to the parcel level regressions, with the sub-parcel hedonic regression estimating that a one-acre increase of any cropland type will result in an approximate $0.56 increase in the price per acre for that cropland type. However, we assumed that the per acre price of a parcel would decrease as the parcel size increased. As parcel size increases, the number of buyers who have the means to purchase the parcel decreases. This may lead to a "bulk rate" discount since there are few potential buyers for a very large parcel. Larger parcels also have lower transaction costs compared to smaller parcels, and therefore sellers will be willing to accept less for their land. However, our results could be attributed to the fact that larger parcels have a more efficient scale of production than smaller parcels. Crop planting and harvesting requires massive amounts of capital for large farming operations. Larger parcels allow for the fixed costs to be spread out over a large area, and therefore larger parcels may be more attractive for growers.

Across all models, the estimate for income was positive and statistically significant. The results indicate that a $1 increase in average per capita income will increase average cropland prices by approximately $0.10 to $0.11 per acre in the parcel level hedonic regression and spatial error model. The sub-parcel hedonic regression indicates an increase of around $0.10 per acre for a $1 increase in per capita income. For the year of sale variables, the year 2015 is the reference category. All year of sale variables are statistically insignificant except for the year 2016 variable in the sub-parcel hedonic model. The finding for the models is expected since there was little change in crop prices throughout the time period.

CONCLUSION

The analysis conducted on cropland values in the state of Mississippi is the first of its kind that we are aware of. The information garnered from this study is of great importance for land buyers and sellers in the state and the surrounding region. This study will make land owners and buyers aware of the value of location, soil, and irrigation characteristics of cropland. The results are at a parcel and sub-parcel level, which gives more accurate estimates than studies conducted at a county level.

The results indicate that soil quality and irrigation significantly affect cropland values. Although our study does not explicitly estimate the value of soil productivity or soil class, the land classes in this study consider soil quality due to the land classes being partly differentiated on their capability of producing crops that are more intensely managed than others (i.e., cotton vs. grain). Therefore, the results of this study are similar to previous studies that estimate that soil quality positively affects cropland values (Huang et al., 2006; Bastian et al., 2002; Drescher, Henderson, and McNamara, 2001). The results also show that well-drained soils in the state are valued higher than other soils. We are not aware of any studies estimating the value of the depth of the nearest wet soil layer on cropland; however, Palmquist and Danielson's (1989) study of North Carolina farmland estimated a $374 per acre price reduction if land required drainage in order to be farmed. Farms in the Delta region of Mississippi are prone to flooding due to flat terrain, and the results are most likely capturing the value that delta growers place on well-drained soils. Also, the slope gradient of cropland plays a significant role in the value of cropland. This was expected since previous studies of slope (Ervin and Mill, 1985) indicate that slope negatively affects cropland values. Also, studies of soil erosion and potential erosivity (Miranowski and Hammes, 1984; Palmquist and Danielson, 1989), which is influenced by slope, found that current and potential erosion reduced farmland values.

The influence of urban areas and income has been documented in previous studies (Delbecq, Kuethe, and Borchers, 2014; Patton and McErlean, 2003), with the studies acknowledging that farmland near urban areas tends to have higher values than rural farmland due to returns from future development and greater access to markets. The results of this study are similar to previous studies since it concludes that cropland near urban areas has a significantly higher value than rural land, *ceteris paribus*.

To our knowledge, no study of cropland values has been conducted at a sub-parcel level. Within-parcel land differences such as soil quality and irrigation techniques are accounted for, and it was expected that doing so would result in a more accurate estimate of the market value that each characteristic has. However, besides the estimate rendered for the Delta variable, the results of the sub-parcel level hedonic model are not largely different than the parcel level hedonic and spatial error model. Therefore, models that incorporate parcel level data may produce similar results to those that use sub-parcel level data.

The results for the spatial error model indicate a strong need for a spatial component in the regression. However, the estimates rendered in the spatial error model are fairly similar to the estimates in the hedonic regression. The argument can be made that the models render the same "big picture" results and the need for complex models is not necessary. However, caution should be exercised since spatial correlation exists in the data used in this paper, and ignoring it in favor of more simple econometric models can render inefficient estimates.

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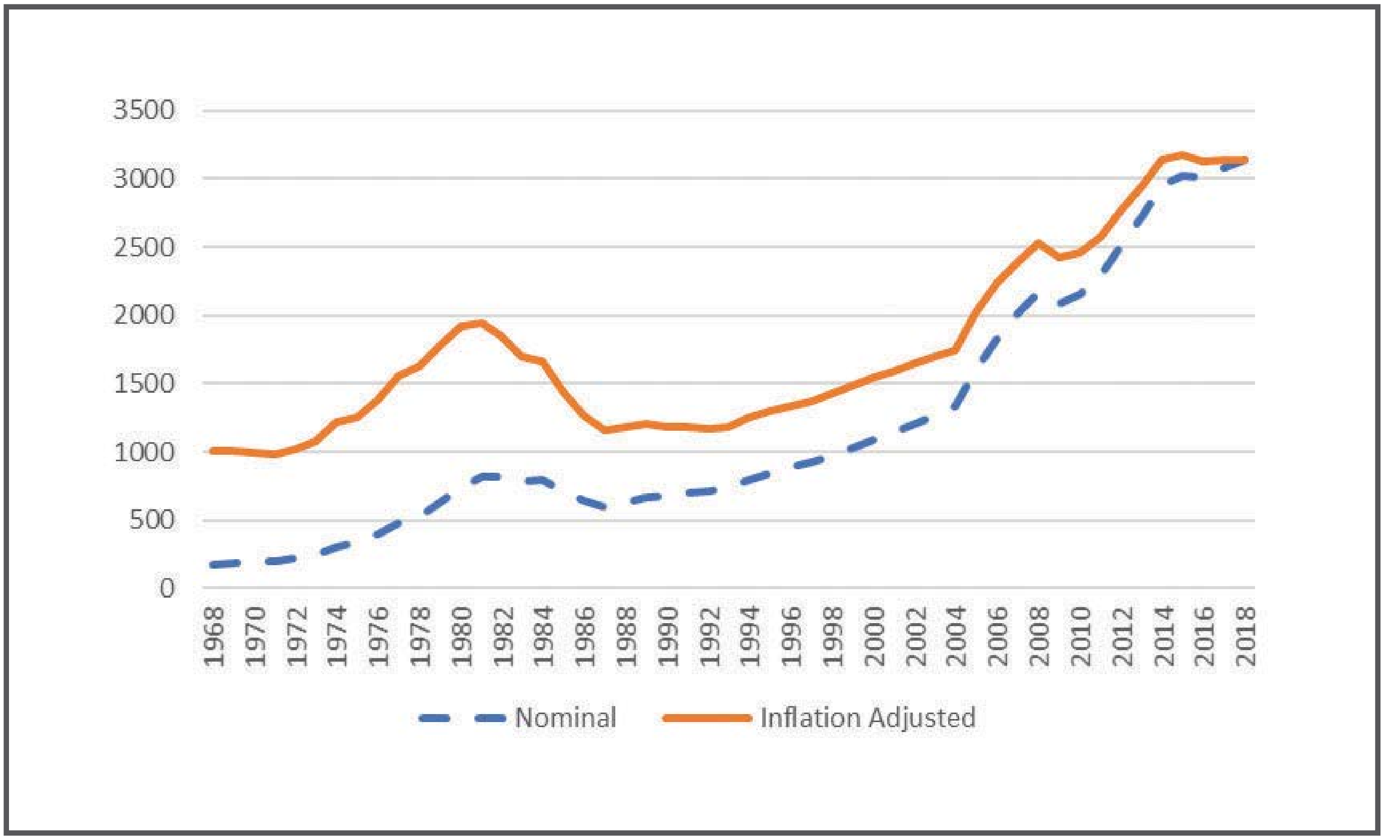

Figure 1. Average U.S. Farm Real Estate Value, 1968–2018 (Data source: Economic Research Service, 2018)

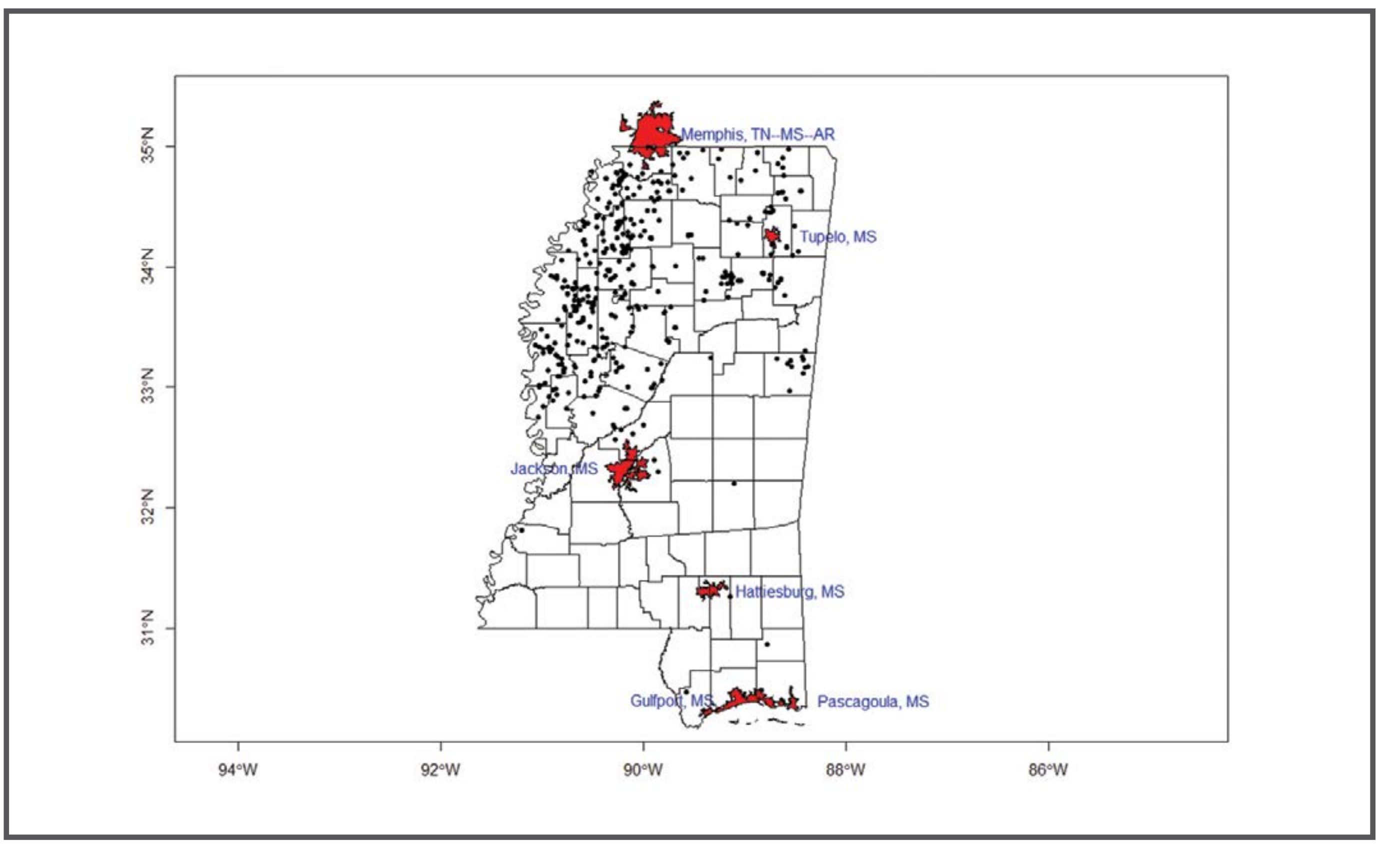

Figure 2. Location of Sales

Table 1. Variable Definitions

Variable	Definition
Acres	Cropland acres within parcel
AWS (cm.)	Available water storage
Slope (%)	Average slope gradient
Wet-Depth (cm.)	Depth to nearest wet soil layer
Cropland 1	Non-irrigated; best suited to cotton or corn
Cropland 2	Non-irrigated; best suited to grain production
Irrigated Cropland 1	Flood irrigated, precision leveled soil
Irrigated Cropland 2	Furrow irrigated; best suited to cotton or corn
Irrigated Cropland 3	Furrow irrigated; best suited to grain production
Irrigated Cropland 4	Pivot irrigated; best suited to cotton or corn
Irrigated Cropland 5	Pivot irrigated; best suited to grain production
Urban10	Dummy variable for urban land sales
Income ($)	Average per capita income of each county
Delta	Dummy variable for land sales in Delta region
year2016	Dummy variable for sale occurring in 2016
year2017	Dummy variable for sale occurring in 2017

Table 2. Land Types and Prices

Land Type	Min. ($/Acre)	Median ($/Acre)	Mean ($/Acre)	S.D. ($/Acre)	Max. ($/Acre)	Obs.
Irrigated Crop 1	2500.00	4730.75	4656.25	759.27	6550.00	51
Irrigated Crop 2	2995.31	4425.00	4391.58	819.82	5783.00	30
Irrigated Crop 3	2400.00	4001.00	4004.34	717.96	5700.00	40
Irrigated Crop 4	2343.76	4000.00	4157.81	1081.69	5495.00	8
Irrigated Crop 5	3050.00	3882.12	3903.21	614.90	4711.43	7
Cropland 1	842.50	3093.80	3296.50	1186.56	7200.00	154
Cropland 2	1200.00	2909.20	2909.36	902.58	6600.00	89

Table 3. Moran's I Test for Spatial Autocorrelation

Distance Restriction	Statistic	Expectation	P-Value
25 Miles	0.375	−0.003	<0.0001
50 Miles	0.286	−0.003	<0.0001
100 Miles	0.232	−0.003	<0.0001

Table 4. Complete Regression Results			
Variable	**Parcel Level Hedonic Model**	**Spatial Error Model**	**Sub-Parcel Hedonic Regression**
Acres	0.448***	0.396***	0.557***
	(0.146)	(0.143)	(0.202)
AWS	-7.427	-0.651	
	(18.743)	(19.333)	
Slope	-77.024***	-72.414***	
	(19.391)	(19.891)	
WTA	8.375***	8.313**	
	(3.115)	(2.934)	
Cropland 2	-397.84***	-349.369***	-768.007***
	(133.72)	(124.624)	(169.813)
Irrigated Cropland 1	1067.50***	1112.765***	1111.08***
	(170.43)	(162.942)	(177.546)
Irrigated Cropland 2	750.91**	728.336***	980.617***
	(244.88)	(199.332)	(212.471)
Irrigated Cropland 3	680.30***	609.497***	519.202**
	(165.36)	(173.384)	(187.621)
Irrigated Cropland 4	895.63*	874.143**	373.519
	(539.60)	(353.422)	(507.434)
Irrigated Cropland 5	16.253	232.409	-177.937
	(343.33)	(377.061)	(486.252)
Urban10	300.62	541.868***	414.097*
	(286.36)	(210.301)	(250.064)
Income	0.111***	0.098***	0.096**
	(0.014)	(0.014)	(0.038)
Delta	643.05***	353.863*	1108.582***
	(126.42)	(192.333)	(167.613)
year2016	153.37	142.278	254.232*
	(113.11)	(100.44)	(132.441)
year2017	51.999	43.229	41.099
	(116.82)	(102.424)	(149.326)
λ		0.747***	
R^2	0.497	0.598	0.396

*p < 0.10; **p < 0.05; ***p < 0.01.

Note: Standard errors are given in parenthesis.

Note: Statistical significance of λ is based on likelihood ratio test.

A Case Study of Upstate New York Landlocked and Restricted Access Land Values

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Abstract

Tracts of land that have no legal or physical access from a public road or right-of-way are occasionally found in rural settings, as well as in suburban and urban neighborhoods. The value of land is directly related to its utility, which is based on the legally permissible and physically possible uses. Sales of landlocked land are rare because potential buyers of land that cannot be accessed are rare. This market study has been formatted so that it can be used as an exhibit in an appraisal report to support adjustments for access-challenged land in Upstate New York. The study shows that discounts up to 90% from typical road-front access land values can be used to estimate landlocked land values. Similarly, discounts up to 75% off the values of road-front access land are applicable to estimate land values with right-of-way or physically restricted access. Appraisers from other regions can follow the analysis format in this paper to develop relevant studies that reflect discounts for restricted access land in their regions.

INTRODUCTION

Tracts of land that have no legal or physical access from a public road or right-of-way are occasionally found in rural settings, as well as in suburban and urban neighborhoods. The value of land is directly related to its utility, which is based on the legally permissible and physically possible uses. So how do we value land that we cannot get to?

Sales of landlocked land are rare because potential buyers of land that cannot be accessed are rare. Usually the buyer of a landlocked tract of land is an abutting or adjoining owner that already has legal and physical access.

There are two thoughts on the value of landlocked land to an adjoining owner. One version is that because the potential market is limited to only the abutting owners (usually ranging from one to a few), the demand is relatively low, which results in a comparatively low price. The second version is that the landlocked parcel is worth more to the abutting owner than to anyone else (in the world).

New York State agencies occasionally sell surplus land that has limited or no independent access except to adjoining owners, such as Canal Corporation land along navigable rivers and lakes. This Canal Corp. land may not be landlocked because the surplus parcels sometimes have limited access from public sources (other than the obvious access from the navigable water); however, such legal or physical access may be limited to a narrow strip along the water frontage. When an abutting owner is interested in purchasing this type of surplus land, the

State requires a "before and after appraisal" in which the adjoining parcel is first appraised by itself in the before appraisal and then the combined adjoining parcel and State land parcel are appraised together in the after appraisal. The difference between the two appraised values is the contributory or enhancement value of the State land, which usually includes direct water frontage. The contributory value is the price the abutting landowner pays for the State land. Similar procedures for surplus land transfers are followed by the New York State Department of Transportation, the New York State Thruway Authority, and other State agencies involving different types of surplus land but usually without the water frontage enhancement.

The common element with each of these State surplus land transfers is that there is usually only one buyer—the abutting landowner—which compromises the willing buyer component of the definition of market value. Sometimes the State surplus land can provide greater utility to the abutting parcel, such as building expansion or added parking, whereas in other situations the surplus land serves only as additional green space.

However, when a parcel of land is truly landlocked, meaning that it has no legal or physical access, the landlocked parcel has little to no utility when considered as a stand-alone tract of land because the owner cannot get to it to grow crops, cut timber, use for recreation, construct a building, or any other type of use. In other words, no feasible development of the land is considered practical. (Note: This does not include landlocked land that adjoins publicly owned land, which gives the general public the right to cross by foot or, in some cases, recreational vehicles such as snowmobiles or all-terrain vehicles.)

METHODOLOGY

The original appraisal problem involved a tract of landlocked recreational land that was proposed to be acquired by a State agency to add to a tract of State Forest land. Considering the landlocked status of the land parcel being examined, our research concentrated on sales of land that lacked legal and physical access in the same neighborhood. Finding none, sales research was expanded to other similar areas in Upstate New York and then to a wider search of urban, suburban, and rural areas, to find sales of landlocked land of any type—commercial, industrial, residential, agricultural, and/or recreational—for the purposes of analyzing values of landlocked land compared to land with similar zoning that had access. Sales of landlocked land were still few in number, so the search was again expanded to include sales with limited, restricted, or right-of-way access. After the first assignment of landlocked recreational land was completed, subsequent assignments of landlocked or restricted access land were presented. Each new appraisal assignment included updated sales searches for more parcels of restricted access land and matched pairs analyses, resulting in the compilation of this market study.

Our study includes 13 sets of vacant land sales without legal and/or physical access in several Upstate New York counties:

1. One sale of commercial land with restricted access in the city of Syracuse in Onondaga County
2. Three sales of commercial land with no legal access in the suburban area of the city of Cortland and town of Cortlandville in Cortland County
3. One sale of industrial land without physical access in the town of Ontario in Wayne County
4. One sale of commercial land without physical access in the town of Avon in Livingston County
5. Four sales of land with right-of-way access in the towns of Greene, German, and McDonough in Chenango County
6. Three sales of residential land with no legal access in the city of Syracuse in Onondaga County
7. One sale of residential land with no legal access in the town of Wilton in Saratoga County
8. One sale of commercial land with no legal access in the village of Bath in Steuben County
9. One sale of wooded recreational land in the town of Stratford in Fulton County that was sold twice in 10 years—first with assumed access and second with no legal access
10. One sale of wooded land partly zoned for commercial that is adjacent to the Route 9 corridor and partly zoned residential next to a manufactured home park located in the town of Moreau in Saratoga County that has legal access only by a right-of-way
11. One sale of agricultural land with open zoning that is near Fry Road in the town of German in Chenango County that has access by a right-of-way
12. One sale of agricultural land with rural zoning that is near Route 414 in the town of Galen in Wayne County that is landlocked
13. One sale of agricultural land with rural zoning near Main Road in the town of Locke in Cayuga County that has physically restricted access

For each of these landlocked or restricted access land parcels, a matched pairs analysis was completed, comparing the range of sale prices of the landlocked/right-of-way/physically restricted access sale to the range of sale prices of similar use (zoned) land sales with road frontage in the same neighborhoods, in order to extract the market-derived discount for the lack of road-front access. The following tables summarize the sale price information for each set of the matched pair sales found in this research. A map is included with each set of sales to show the location of the test property and the control sales used in each analysis. Complete sale data sheets are retained in the appraiser's files and can be provided upon request.

Control sales were identified that were similar in all physical characteristics and general location except for the type and quality of access. It is also recognized that lack of road-front access usually is paired with lack of electricity and other available public utilities (water, sewer, and/or gas for urban and suburban locations). Other than the type of access, the only significant difference between the control sales and the test sale was for the time differences between the sale dates. The land sales in the tables have been adjusted for time by trending the sale prices to the same date based on a 1% per year time adjustment (adjusted to the most current sale date of the landlocked or restricted access sales). The authors' study of time trends throughout Upstate New York for the past 10 years indicates that land prices have appreciated from about 0% to 3% per year; therefore, an overall rate of 1% per year, compounded annually, is reasonable for this market study. The last column in each table shows the unit price of each respective sale, after time adjustment, with the overall average and median unit prices for each set of sales calculated. The last rows of each table show the unit price discount from typical access land to the specific restricted access land for the average unit prices, median unit prices, and maximum range (highest typical access land sale to lowest restricted access land sale).

1. Onondaga County: Restricted Access Commercial Land

A sale of commercial land with access by right-of-way was identified in the eastern part of the city of Syracuse (Onondaga County) off Erie Boulevard East (Figure 1 and Table 1, Sale 1-A). Seven sales of commercial land with typical road-front access were identified in the same area (Figure 1 and Table 1, Sales 1-B through 1-H). The only significant differences between the two groups of sales were the sale dates, availability of utilities, and quality of access for Sale 1-A. Each of the sales were adjusted for time at 1% per year by adjusting Sales 1-B through 1-H to the sale date of restricted access sale (Sale 1-A).

2. Cortland County: Legally Landlocked Commercial Land

Three sales of commercial land that were legally landlocked were identified in the town of Cortlandville in Cortland County at the intersection of Route 281 and McLean Road as remnant parcels following the New York State Department of Transportation (DOT) road-widening project of Route 281 (Figure 2 and Table 2, Sales 2-A through 2-C). Sale 2-A was the land remnant remaining from a service station that was acquired for the road project; it sold with no legal or physical access to either fronting road. The State purchased the land at the appraised value as landlocked land. Sales 2-B and 2-C are the same parcel, originally a different service station located on the opposite corner, which was similarly created by the same DOT road project. The State purchased the remnant from the owner at the appraised value in 2008, then sold it to an adjoining owner for an appraised and negotiated price in 2016. Four sales of commercial land with typical road-front access were identified in the same area (Figure 2 and Table, 2, Sales 2-D through 2-G). The only significant differences between the two groups of sales were the sale dates, availability of utilities, and quality of access for Sales 2-A, 2-B, and 2-C. Each of the sales were adjusted for time at 1% per year. Sales 2-D through 2-G were adjusted to the sale date of the most recent landlocked access sale (Sale 2-C).

3. Wayne County: Industrial Land without Physical Access

A sale of industrial land without physical access was identified in the town of Ontario in Wayne County (Figure 3 and Table 3, Sale 3-A). The owner of an adjoining parcel that had road frontage purchased this parcel. Three sales of industrial land with typical street frontage were found in the same neighborhood (Figure 3 and Table 3, Sales 3-B through 3-D), with the only significant differences being the sale dates, availability of utilities, and quality of access. The matched pair sales were adjusted for time to the restricted access sale's date at 1% per year. Sales 3-B through 3-D were adjusted to the sale date of the restricted access sale (Sale 3-A).

4. Livingston County: Commercial Land without Physical Access

A sale of commercial land without physical access was identified in the town of Avon in Livingston County (Figure 4 and Table 4, Sale 4-A). This parcel lacked road access and was purchased by a neighboring owner. Six sales of similar commercial land with typical public road access were found in the same town and adjoining towns (Figure 4 and Table 4, Sales 4-B through 4-G), with the only significant differences being the sale dates, availability of utilities, and quality of access. The matched pair sales were adjusted for time to the sale date of the restricted access sale (Sale 4-A).

5. Chenango County: Restricted Access Recreational Land

Four sales of recreational land with right-of-way access were identified in Chenango County (Figure 5 and Table 5, Sales 5-A through 5-D). Each of these sales consisted of rural wooded land that lacked physical access to public roads but did have legal access via rights-of-way. Five sales of similar recreational land were identified in the same area (Figure 5 and Table 5, Sales 5-E through 5-I) that had frontage on public roads, with the only significant differences being the availability of utilities, quality of access, and sale dates. All of the sales were adjusted to the most recent sale date of the restricted access sales (Sale 5-A).

6. Onondaga County: Landlocked Residential Land

Three sales of residential land without legal or physical access were identified in the southwestern quadrant of the city of Syracuse in Onondaga County (Figure 6 and Table 6, Sales 6-A through 6-C). Each of these sales consisted of vacant wooded land in residential neighborhoods that were in rear locations without road frontage and considered to be landlocked. The surrounding urban neighborhoods are almost 100% built up, which is typical for cities; however, four sales of residential land were identified in the same neighborhoods (Figure 6 and Table 6, Sales 6-D through 6-G) that had road frontage, with the only significant differences being the availability of utilities, quality of access, and sale dates. All of the sales were adjusted to the most recent sale date of the landlocked sales (Sale 6-C).

Sale 6-D represents the sale of a parcel of vacant land in proximity to the three landlocked parcels and is included in this analysis to represent the possible maximum discount for access adjustments. The results for the indicated discounts in this market are illustrated with and without this sale not only to illustrate the potential effect of access limitations but also to illustrate the likely discount without this individual sale's influence.

7. Saratoga County: Landlocked Residential Land

One sale of residential land that was landlocked was identified at the rear of Parnil Drive in the town of Wilton in Saratoga County (Figure 7 and Table 7, Sale 7-A). This parcel was sold on February 8, 2012, for $6,000. Two sales of residential land with road-front access in the same neighborhood transferred in 2015 and 2013 (Table 7, Sales 7-B and 7-C). The prices of the road-front sales were adjusted for time at 1% per year to the landlocked sale (Sale 7-A). The discounts for landlocked access are calculated in Table 7.

8. Steuben County: Landlocked Commercial Land

A 1.03-acre parcel of commercial land with no access that was located off Geneva Street (Route 54) in the village of Bath in Steuben County was sold on August 24, 2015, for $5,000 (Figure 8 and Table 8, Sale 8-A). A nearby 0.46-acre lot of commercial land with road-front access sold within five days of Sale 8-A for $27,500 (Sale 8-B), requiring no time adjustment. The discounts for landlocked access are calculated in Table 8.

9. Fulton County: Landlocked Recreational Land

One sale of wooded recreational land consisting of 100 acres located off Middle Sprite Road in the town of Stratford in Fulton County sold twice over a 10-year period (Figure 9 and Table 9), with one significant difference in the parcel's characteristics between sale dates being its quality of access. This property first sold in 2008 for $82,500, or $825 per acre, with the assumption that it had legal access across adjoining State-owned land. However, when preparing to cut timber on this parcel, the owner was informed that the property had no legal access across the State land. According to the seller's broker, the grantor sued the title company and won, proving that this parcel did not have any access across the State land and could only get such access by a temporary revocable permit. Foot and snowmobile access are available across the State land but are not designated as a deeded right-of-way to the property. The owner sold the property in 2017 for $25,000, or $250 per acre, with the landlocked status known to the buyer. As a result, this same parcel was sold twice over a 10-year period—first with assumed access and second with no known legal access. The 2008 sale price is adjusted for time at the rate of 1% per year. The two transactions of this parcel are identified as Sales 9-A and 9-B. The discounts for landlocked access are calculated in Table 9.

10. Saratoga County: Commercial/ Residential Land with Right-of-Way Access

One sale of wooded commercial/residential land consisting of 22 acres located off Route 9 in the town of Moreau in Saratoga County was identified (Figure 10 and Table 10, Sale 10-A). This parcel was sold in late 2017 for $40,000, or $1,818 per acre (following a recent appraisal of $44,000). The parcel is zoned commercial along its western half near the Route 9 corridor. Its only access is a legal right-of-way to and from Route 9. The eastern half is zoned residential and is adjacent to a manufactured home park. The grantee is the owner of the adjacent manufactured home park who acquired the land as a buffer and for possible expansion. Six sales of similar land were identified in the same marketing area (Sales 10-B through 10-G), with five zoned for residential use and one (Sale 10-D) zoned for commercial use. The matched pair sales were adjusted for time at 1% per year to the date of the restricted access land sale (Sale 10-A). The discounts for right-of-way access are calculated in Table 10.

11. Chenango County: Agricultural Land with Right-of-Way Access

One sale of agricultural land consisting of 23 acres located off County Road 2 in the town of German in Chenango County was identified (Figure 11 and Table 11, Sale 11-A). This parcel was sold in January 2016 for $12,000, or $522 per acre. The parcel is in an area without zoning. Its only access is a legal right-of-way to and from County Road 2. The grantee is not an adjacent owner. Five sales of similar land were identified in the same marketing area (Sales 11-B through 11-F), with no significant differences in zoning and with similar physical characteristics. The matched pair sales were adjusted for time at 1% per year to the date of the right-of-way access land sale (Sale 11-A). The discounts for right-of-way access are calculated in Table 11.

12. Wayne County: Landlocked Agricultural Land

One sale of agricultural land consisting of 79.79 acres located off Route 414 in the town of Galen in Wayne County was identified (Figure 12 and Table 12, Sale 12-A). This parcel was sold in March 2017 for $128,500, or $1,610 per acre. The parcel is in an area without zoning. It was previously accessed through a neighboring parcel. The grantee also became an adjacent owner. Four sales of similar land were identified in the same marketing area (Sales 12-B through 12-E), with no significant differences in zoning, land utilization, or soils. The matched pair sales were adjusted for time at 1% per year to the date of the landlocked land sale (Sale 12-A). The discounts for landlocked access are calculated in Table 12.

13. Cayuga County: Physically Restricted Access Agricultural Land

One sale of agricultural land consisting of 45.44 acres located off Main Road in the town of Locke in Cayuga County was identified (Figure 13 and Table 13, Sale 13-A). This parcel was sold in September 2016 for $74,976, or $1,650 per acre. The parcel is in an area without zoning. It has a narrow strip of road frontage that is not physically accessible, so alternative access was acquired by a verbal right-of-way through a neighboring parcel. Six sales of similar land were identified in the same marketing area (Sales 13-B through 13-G). The matched pair sales were adjusted for time at 1% per year to the date of the physically restricted land sale (13-A). The discounts for physically restricted access are calculated in Table 13.

SUMMARY OF DISCOUNTS FOR VALUES OF RESTRICTED ACCESS LAND IN UPSTATE NEW YORK

Twenty sales were identified in nine Upstate New York counties that were either landlocked or lacked legal or reasonable physical access. Table 14 summarizes the comparisons of the unit prices of each of the restricted access sales with sales of similar type land in the same relative areas, grouped by type of restricted access.

The comparison of these 13 sets of restricted access land sales shows a range of discounts from 26% to 97% based on the average and median unit prices. Table 14 shows the overall average of the average and median discounts, followed by the overall median of the average and median discounts. Relative to this sale data, the six groups of landlocked sales exhibited the overall highest discounts, with overall average discounts of the averages and medians of 78% and 81%. The four right-of-way access sale groups reflected overall average discounts of the averages and medians of 77% and 78%, respectively. The three sale groups lacking physical access reflected the lowest discounts, with overall average discounts of the averages and medians of 58% and 45%, respectively.

It is logical that the landlocked land sales would exhibit larger discounts than sales that have right-of-way access or sales that lack physical access except through an adjoining (buyer) parcel.

It is also recognized that the restricted access sales, in addition to lacking road frontage, also lack direct access to the utilities that service the respective area (e.g., electricity in rural areas; electricity, water, sewer, and/or gas in urban and suburban areas—note that cell phones have eliminated the need to have access to telephone wired utility lines).

In conclusion, based on the research in this market study, Upstate New York land parcels that are land-locked exhibit unit values that require a discount typically ranging from about 78% to 81% from the fee simple values of similar type land parcels in the same neighborhoods with full access. Alternatively, land-locked land has a value typically ranging from approx-imately 20% to 25% of the fully accessible land in the same general location.

Also based on the research in this market study, Upstate New York land parcels that have right-of-way or physi-cally restricted access exhibit unit values that typically require a discount ranging from about 65% to 90% from the fee simple values of similar type land parcels in the same neighborhood with full access. However, the overall range of discounts in this category is lower than what was extracted for the landlocked access sales. A reasonable range for the right-of-way or phys-ically restricted lands indicates values that are approx-imately 25% to 50% of the fully accessible land in the same general location. The discount percentages do not appear to be affected by the property types of the matched pair sales.

The discounts for the restricted access sales have also been reviewed based on land type, as summarized in Table 15. The residential land types reflect the highest discounts at 90+% for landlocked restricted access. The range of discounts for the agricultural, recreational, and commercial/industrial land are lower but are generally similar for each type of access, with landlocked land access discounts generally higher than discounts for right-of-way and physically restricted access land.

The landlocked agricultural land (Group 12) appears to be an anomaly compared to the rest of the sale data, with lower discounts relative to the right-of-way access and physically restricted access agricultural land. The reason for this difference could be the stronger demand by large dairy farm operations (sometimes referred to as Concentrated Animal Feeding Operations—CAFO—farms) to continue adding more land, regardless of quality of access, so herd sizes can be expanded.

The findings in this study are predicated on sales ac-tivity mainly within the past decade since the bottom of the national recession, therefore occurring in the moderately expanding market in Upstate New York over that period. There is insufficient data in this study to conclude if the results would be the same or different in a static or retracting economy.

Note: The discount ranges derived in this market study are applicable to Upstate New York for the time period studied. Each appraiser referencing this market study should complete a similar study of matched pair sales analyses in their respective region to evaluate the ap-propriate range of discounts in other areas.

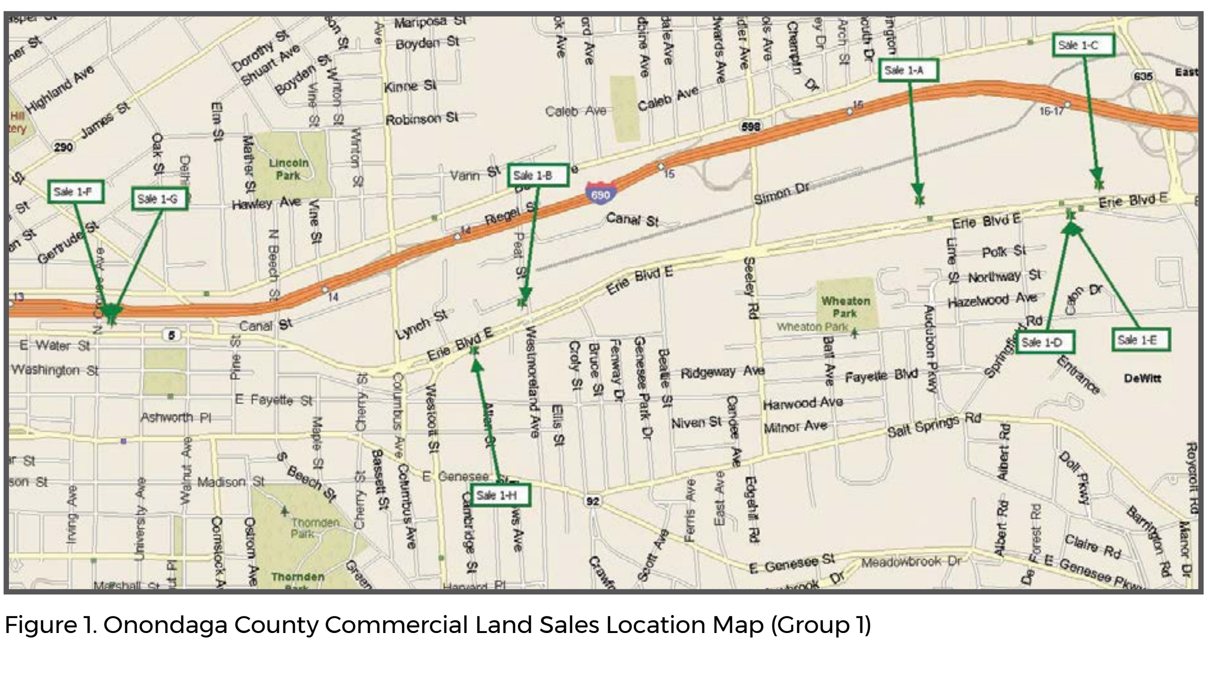

Figure 1. Onondaga County Commercial Land Sales Location Map (Group 1)

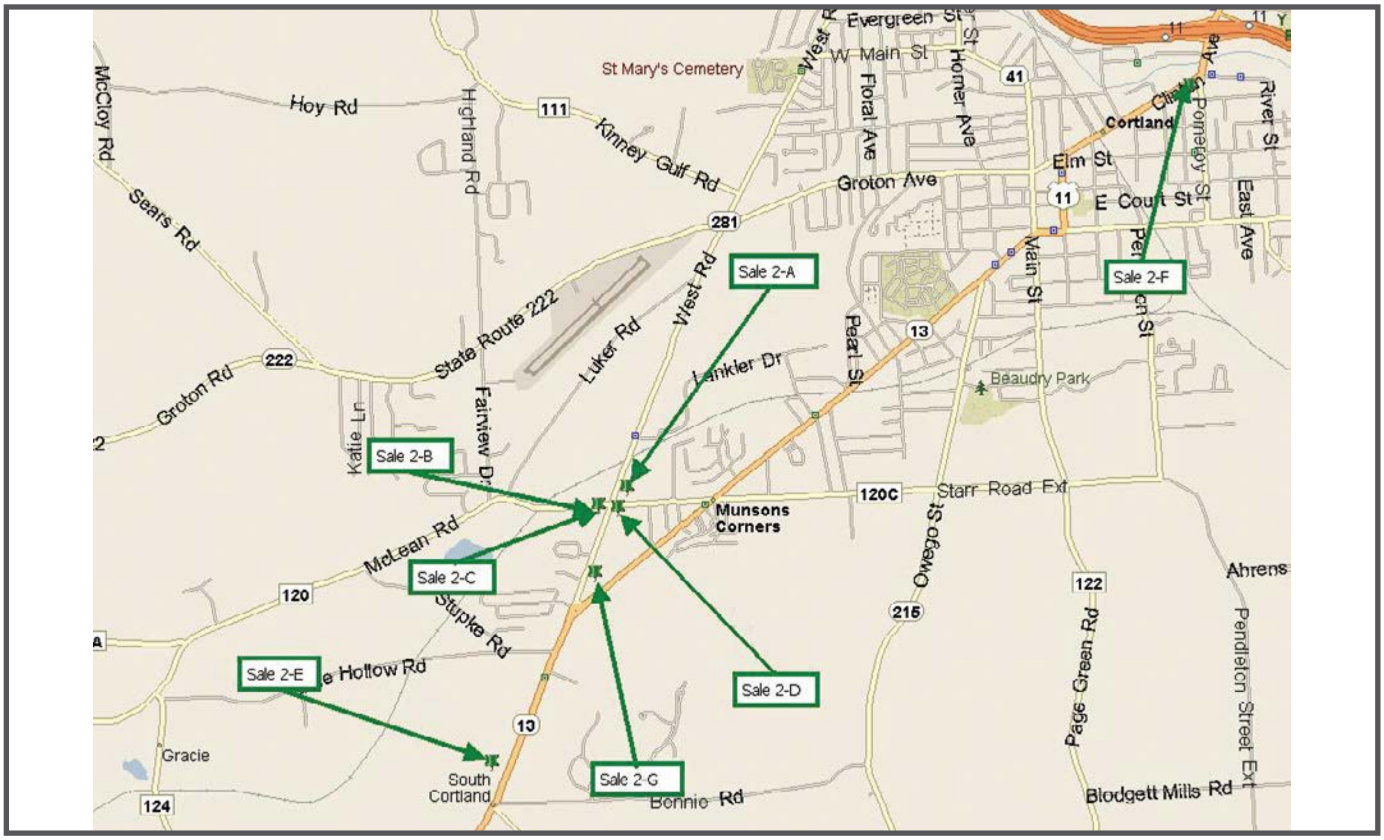

Figure 2. Cortland County Commercial Land Sales Location Map (Group 2)

Figure 3. Wayne County Industrial Land Sales Location Map (Group 3)

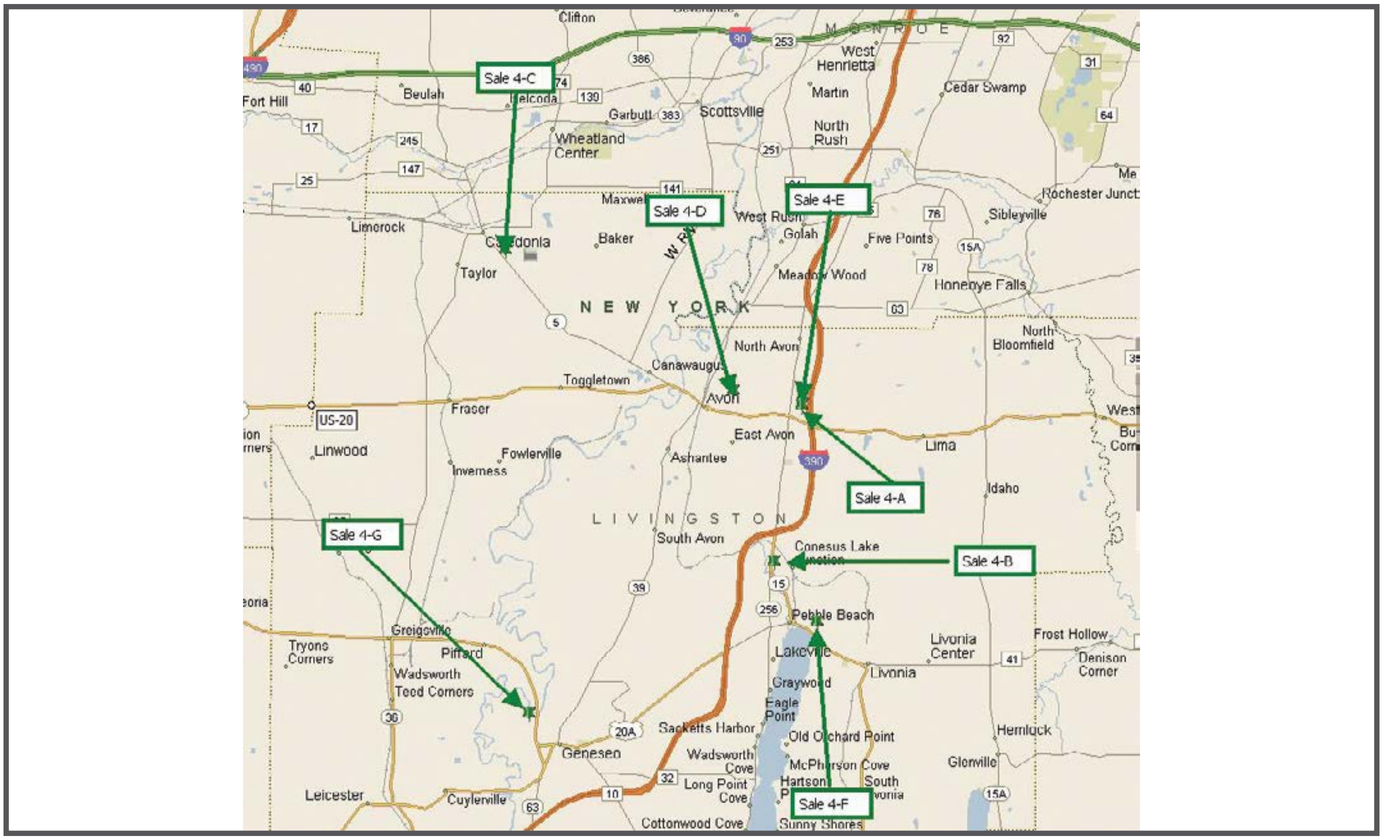

Figure 4. Livingston County Commercial Land Sales Location Map (Group 4)

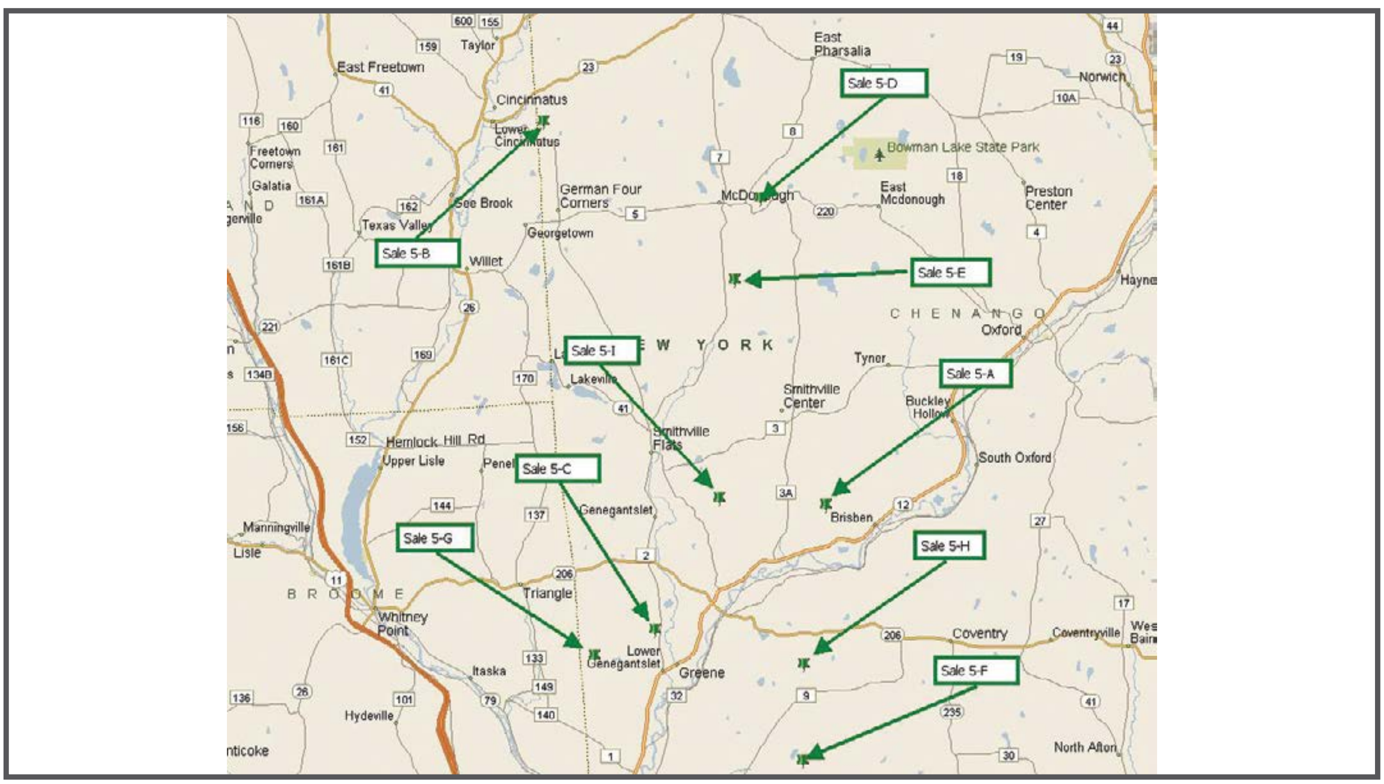

Figure 5. Chenango County Recreational Land Sales Location Map (Group 5)

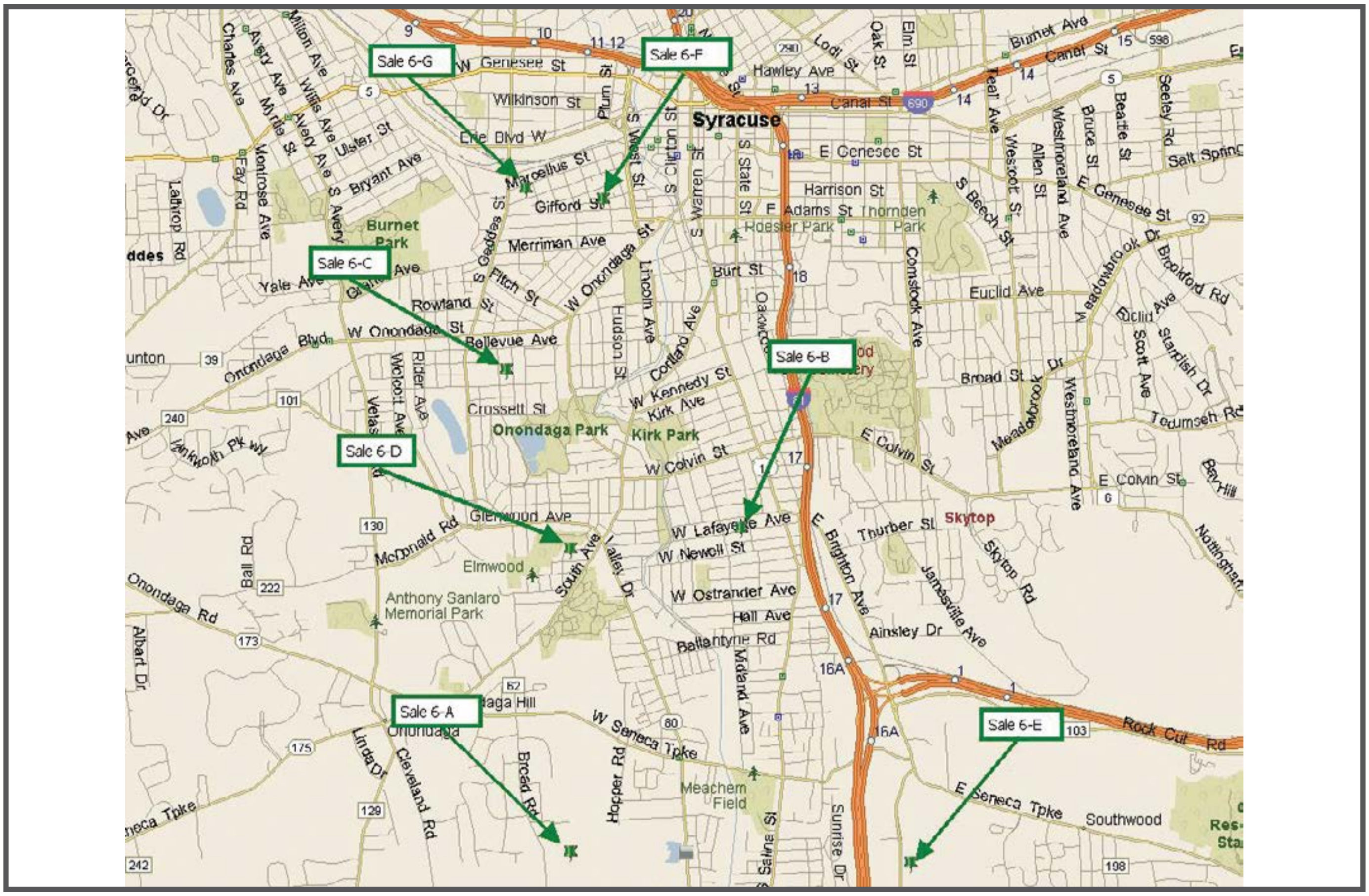

Figure 6. Onondaga County Residential Land Sales Location Map (Group 6)

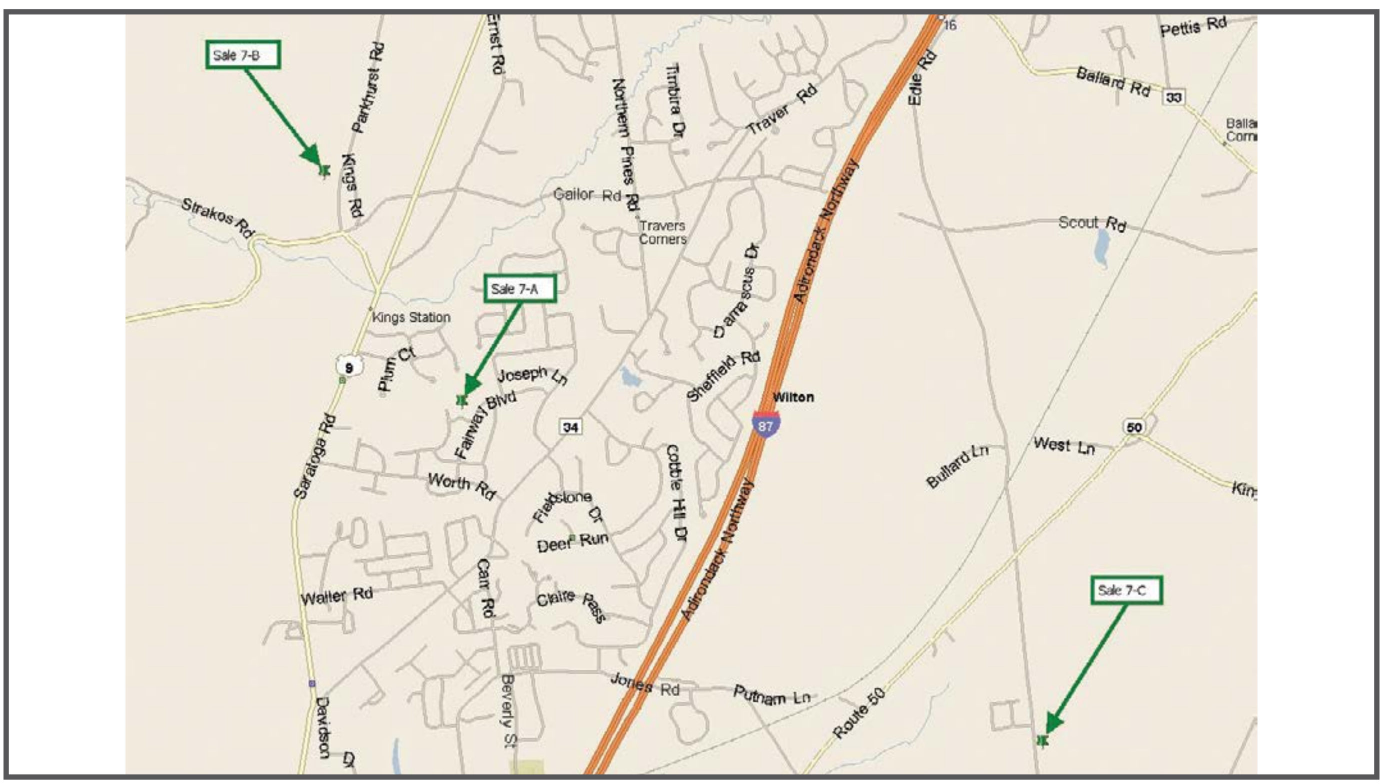

Figure 7. Saratoga County Residential Land Sales Location Map (Group 7)

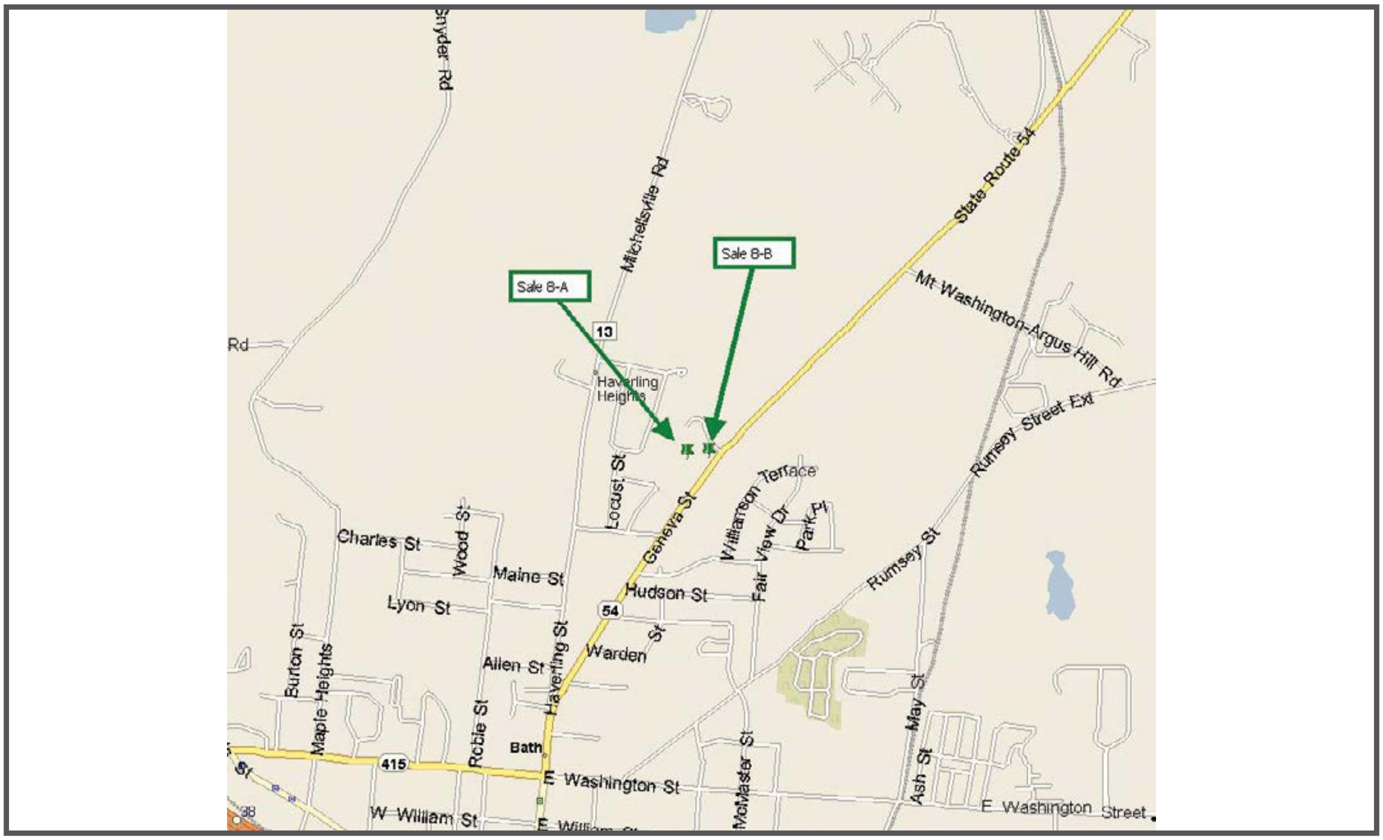

Figure 8. Steuben County Commercial Land Sales Location Map (Group 8)

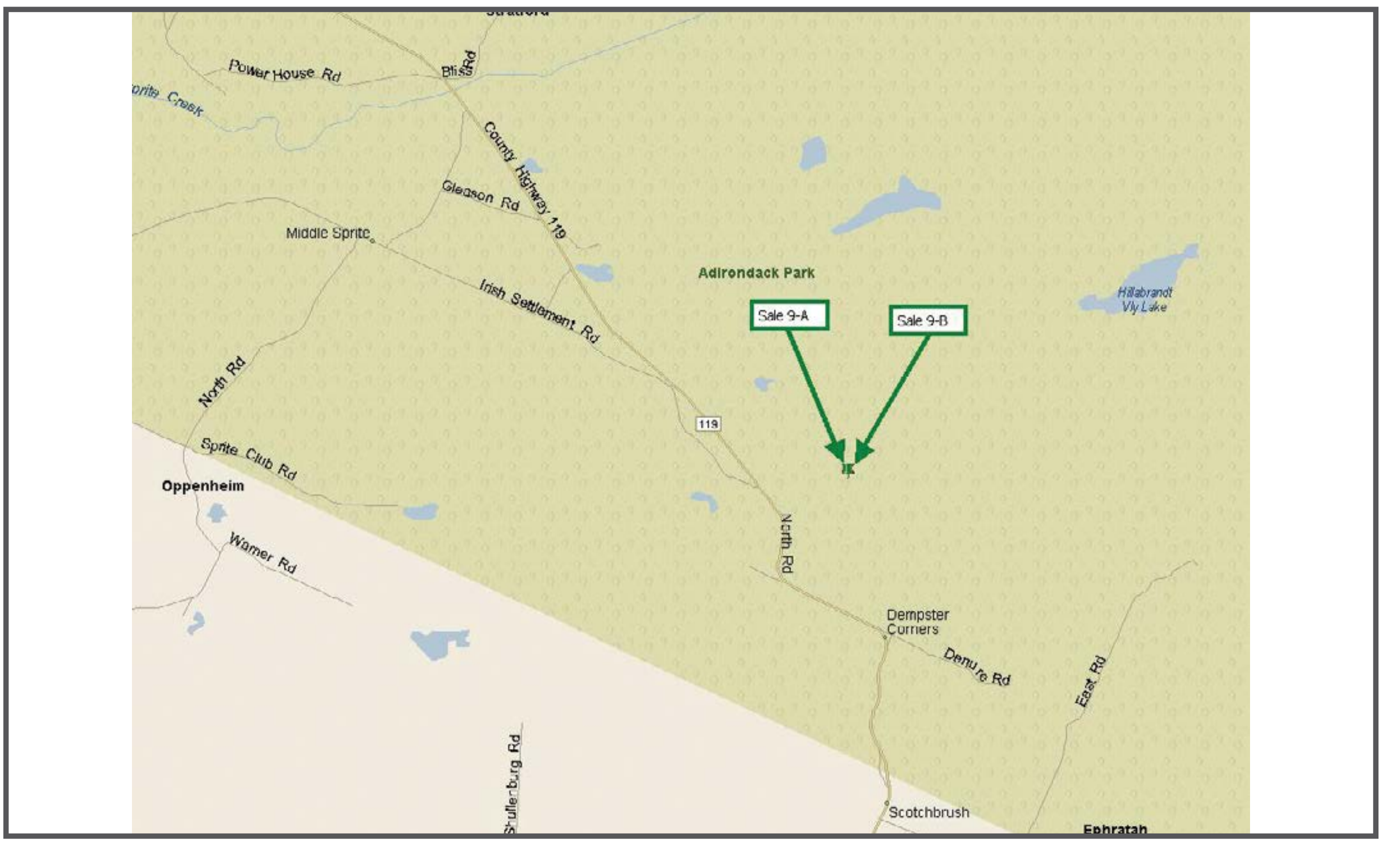

Figure 9. Fulton County Recreational Land Sales Location Map (Group 9)

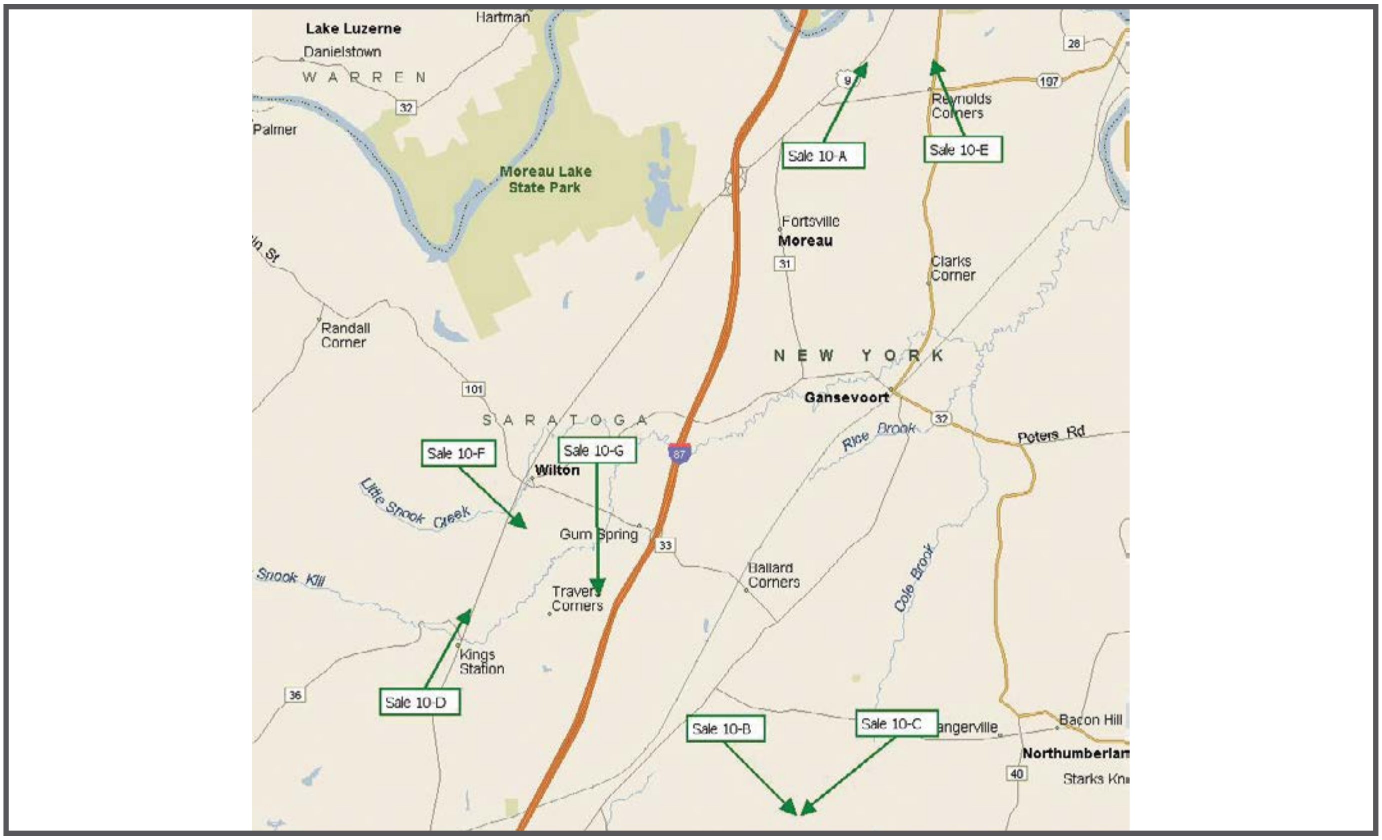

Figure 10. Saratoga County Commercial/Residential Land Sales Location Map (Group 10)

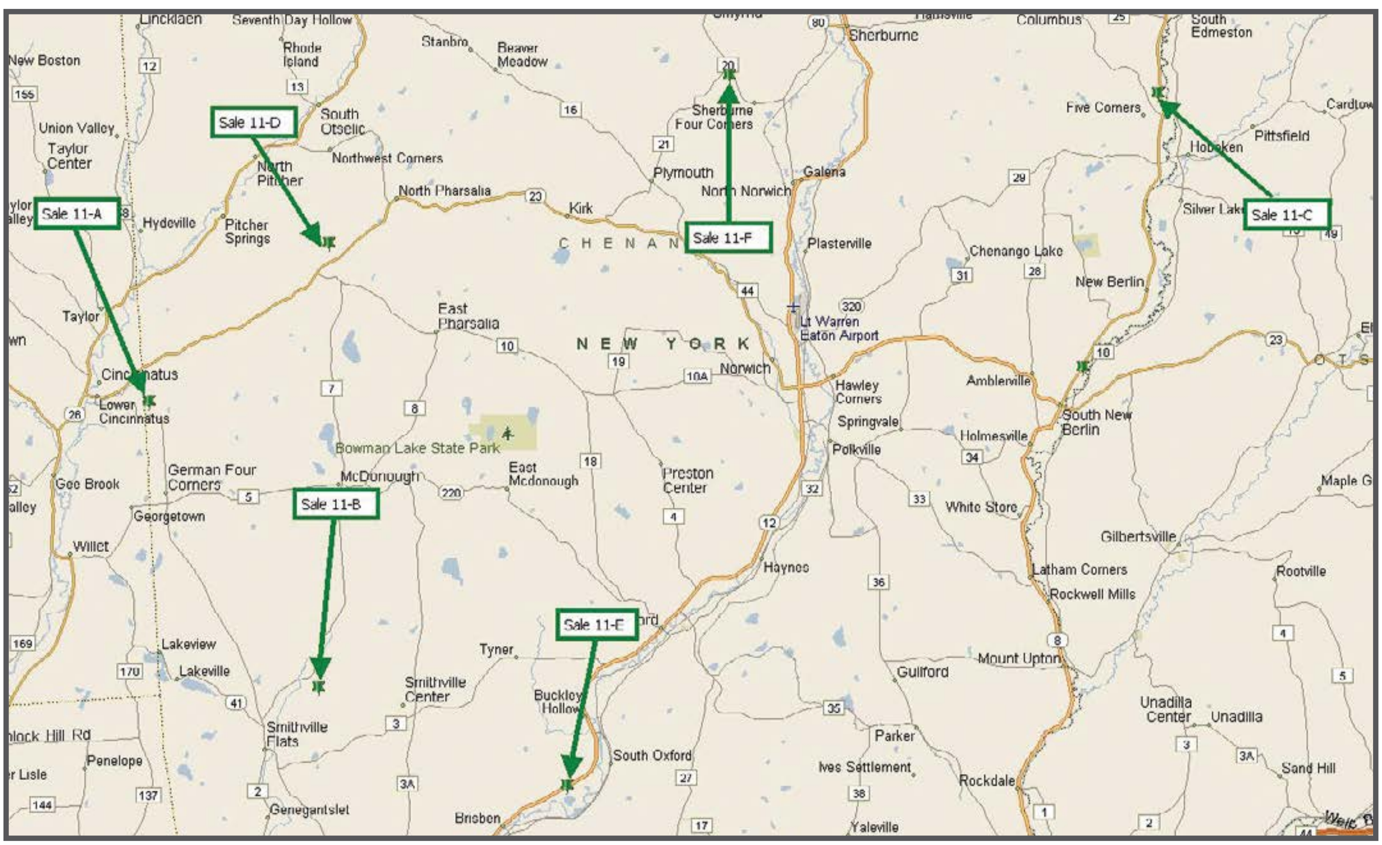

Figure 11. Chenango County Agricultural Land Sales Location Map (Group 11)

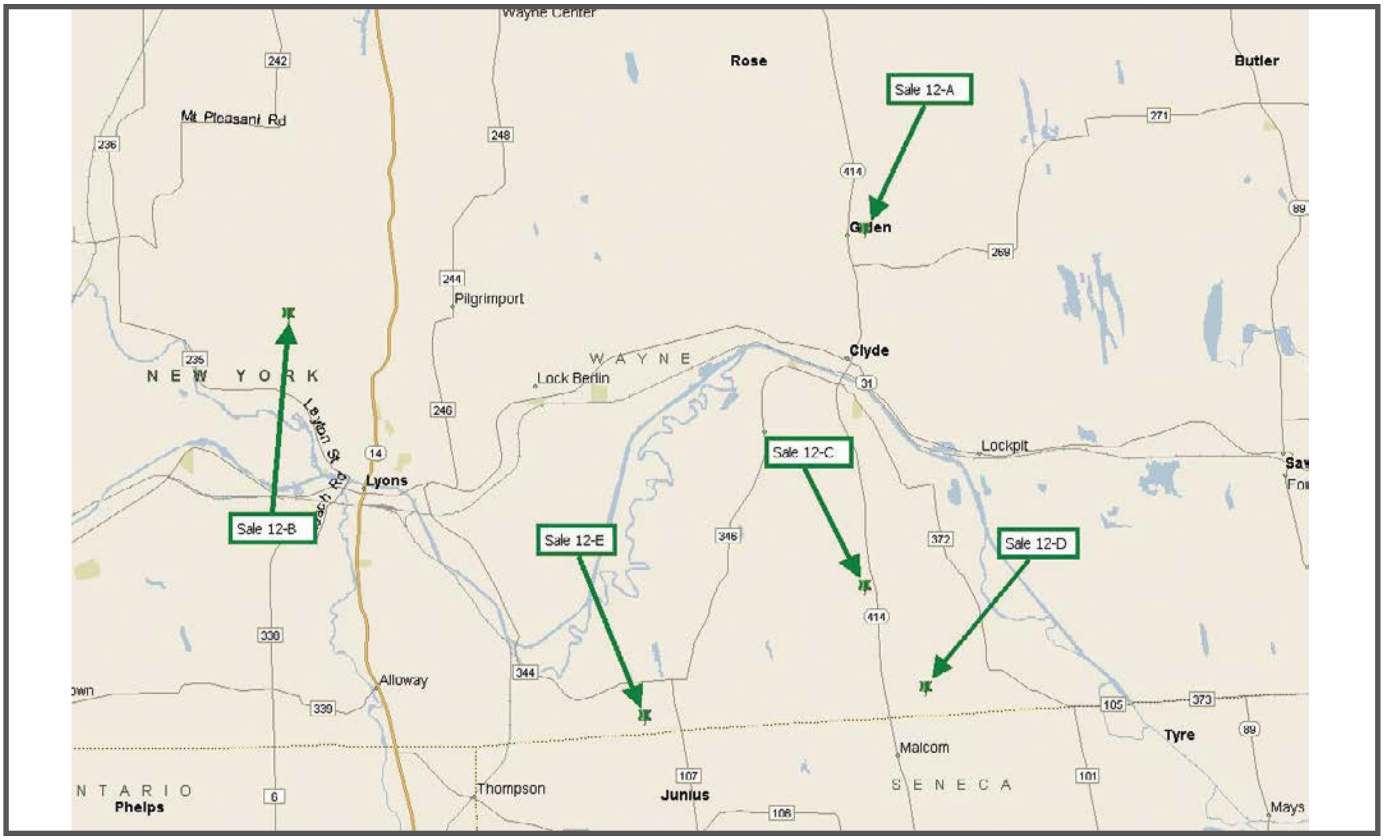

Figure 12. Wayne County Agricultural Land Sales Location Map (Group 12)

Figure 13. Cayuga County Agricultural Land Sales Location Map (Group 13)

Table 1. Onondaga County: Restricted Access Commercial Land										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						4/11/2005		**1%**		
Commercial Land Sales with Right-of-Way Access										
1-A	33.1-1-22.0	Off 2701 Erie Blvd. East	Syracuse	0.44	4883/355	4/11/2005	$25,000	0.00%	$25,000	$56,818
			AVERAGE	**0.44**			**$25,000**		**$25,000**	**$56,818**
			MEDIAN	**0.44**			**$25,000**		**$25,000**	**$56,818**
Commercial Land Sales with Road Access										
1-B	32.1-01-17.0	1915 Erie Blvd. East	Syracuse	1.1	5122/539	4/16/2010	$330,000	-4.87%	$313,929	$285,390
1-C	33.-01-02.0	3017 Erie Blvd. East	Syracuse	2.21	5035/860	2/2/2008	$412,500	-2.76%	$401,115	$181,912
1-D	33.-05-06.0	2934 Erie Blvd. East	Syracuse	0.15	5131/430	7/6/2010	$64,000	-5.08%	$60,749	$404,992
1-E	33.-05-06.0	2934 Erie Blvd. East	Syracuse	0.15	5003/407	7/10/2007	$100,000	-2.21%	$97,790	$651,933
1-F	30.-07-01.2	1021 Erie Blvd. East	Syracuse	0.29	4978/184	1/2/2007	$25,261	-1.70%	$24,832	$85,626
1-G	30.-07-01.2	1021 Erie Blvd. East	Syracuse	0.29	4838/283	7/1/2004	$25,000	0.78%	$25,195	$86,879
1-H	36.-01-07.0	1816 Erie Blvd. East	Syracuse	1	4808/895	11/19/2003	$150,000	1.40%	$152,100	$152,100
			AVERAGE	**0.74**			**$158,109**		**$153,673**	**$207,466**
			MEDIAN	**0.29**			**$100,000**		**$97,790**	**$344,828**
Discount for Right-of-Way Access Based on Average Unit Prices										**73%**
Discount for Right-of-Way Access Based on Median Unit Prices										**84%**
Discount for Right-of-Way Access, Maximum Range										**91%**

Table 2. Cortland County: Legally Landlocked Commercial Land										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						2/24/2016		**1%**		
Commercial Land Sales without Legal Access										
2-A	95.12-01-10.0	3628 Route 281	Cortlandville	0.231	2011/4461	9/14/2011	$15,000	4.52%	$15,678	$67,870
2-B	95.12-01-12.0	3609 Route 281	Cortlandville	0.36	2008/3867	7/11/2008	$27,000	7.88%	$29,128	$80,910
2-C	95.12-01-12.0	3609 Route 281	Cortlandville	0.36	2016/1001	2/24/2016	$25,000	0.00%	$25,000	$69,444
			AVERAGE	**0.317**			**$22,333**		**$23,269**	**$73,402**
			MEDIAN	**0.36**			**$25,000**		**$25,000**	**$69,444**
Commercial Land Sales with Road Access										
2-D	95.12-01-11.0	942 McLean Rd.	Cortlandville	1.96	2016/1517	3/9/2016	$475,000	-0.04%	$474,810	$242,250
2-E	105.08-01-04.0	807 Route 13	Cortlandville	0.44	2011/6585	12/13/2011	$125,000	4.27%	$130,338	$294,881
2-F	86.44-03-01.0	137-143 Route 13	Cortland	0.88	2008/1971	4/7/2008	$400,000	8.16%	$432,640	$491,636
2-G	95.16-01-21.0	927-931 Route 13	Cortlandville	1.16	10457/36002	2/16/2006	$387,500	10.48%	$428,110	$369,060
			AVERAGE	**1.11**			**$346,875**		**$366,474**	**$330,008**
			MEDIAN	**1.02**			**$393,750**		**$430,375**	**$386,029**
Discount for Legally Landlocked Land Based on Average Unit Prices										**78%**
Discount for Legally Landlocked Land Based on Median Unit Prices										**82%**
Discount for Legally Landlocked Land, Maximum Range										**86%**

Table 3. Wayne County: Industrial Land without Physical Access										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						1/28/2016		**1%**		
Industrial Land Sales without Physical Access										
3-A	61117-00-429672	475 Route 104	Ontario	4	917/97903	1/27/2016	$60,000	0.00%	$60,000	$15,000
			AVERAGE	**4**			**$25,000**		**$60,000**	$15,000
			MEDIAN	**4**			**$25,000**		**$60,000**	$15,000
Industrial Land Sales with Road Access										
3-B	61117-00-197676	6298 Dean Parkway	Ontario	1.04	916/96553	11/8/2014	$50,000	1.22%	$50,610	$48,663
3-C	61117-00-110896	249 David Parkway	Ontario	4.19	916/98466	12/18/2014	$70,000	1.11%	$70,777	$16,892
3-D	62117-12-958710	1683 Route 104	Ontario	0.88	917/95701	11/5/2015	$70,000	0.23%	$70,161	$79,728
			AVERAGE	**2.04**			**$63,333**		**$63,849**	**$31,350**
			MEDIAN	**1.04**			**$70,000**		**$70,161**	**$67,308**
Discount for Right-of-Way Access Based on Average Unit Prices										**52%**
Discount for Right-of-Way Access Based on Median Unit Prices										**78%**
Discount for Right-of-Way Access, Maximum Range										**81%**

Table 4. Livingston County: Commercial Land without Physical Access										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						2/22/2012		**1%**		
Commercial Land Sales without Physical Access										
4-A	35-1-13.052	Road A	Avon	5.29	1264/2455	2/22/2012	$66,250	0.00%	$66,250	$12,524
			AVERAGE	**5.29**			**$66,250**		**$66,250**	**$12,524**
			MEDIAN	**5.29**			**$66,250**		**$66,250**	**$12,524**
Commercial Land Sales with Road Access										
4-B	65-1-6.42	Gateway Park	Livonia	3.69	1270/648	11/26/2013	$72,500	-1.74%	$71,239	$19,306
4-C	13.-1-133	Caledonia-Avon Rd.	Caledonia	1.86	1274/2578	6/2/2015	$26,000	-3.21%	$25,165	$13,530
4-D	34.7-1-42.257	604 Collins St.	Avon	4.95	1280/76	9/29/2016	$335,000	-4.48%	$319,992	$64,645
4-E	35.-1-13.527	5700 Tee Dr.	Avon	2.92	1281/2798	4/3/2017	$48,000	-4.96%	$45,619	$15,623
4-F	65-1-98.13	Big Tree Rd.	Livonia	2.75	1282/2309	6/30/2017	$45,000	-5.19%	$42,665	$15,514
4-G	80.-1-18.113	Geneseo St.	Geneseo	6.01	1284/462	10/27/2017	$180,000	-5.49%	$170,118	$28,306
			AVERAGE	**3.7**			**$117,750**		**$112,466**	**$30,424**
			MEDIAN	**3.31**			**$60,250**		**$58,429**	**$18,230**
Discount for Right-of-Way Access Based on Average Unit Prices										**59%**
Discount for Right-of-Way Access Based on Median Unit Prices										**31%**
Discount for Right-of-Way Access, Maximum Range										**81%**

Table 5. Chenango County: Restricted Access Recreational Land										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						9/12/2016		**1%**		
Recreational Land Sales with Right-of-Way Access										
5-A	227.-1-52	Off State Highway 12	Greene	10	2016/1766	9/12/2016	$8,000	0.00%	$8,000	$800
5-B	128.-1-9.5	Off Fry Rd.	German	23	2016/157	1/29/2016	$12,000	0.62%	$12,074	$525
5-C	247.-1-1.32	Off County Road 2	Greene	8.77	2016/36	11/15/2015	$14,000	0.83%	$14,116	$1,610
5-D	155.-1-20.3	Off State Highway 220	McDonough	30.34	2015/682	4/23/2015	$25,000	1.39%	$25,348	$835
			AVERAGE	**18.03**			**$14,750**		**$14,885**	**$826**
			MEDIAN	**16.5**			**$13,000**		**$13,095**	**$794**
Recreational Land Sales with Road Access										
5-E	166.-1-6.21	Creek Rd.	Livonia	10.62	2015/1367	9/1/2015	$16,184	1.03%	$16,351	$1,540
5-F	269.-4-39.1	Wylie & Paradise Valley Rds.	Caledonia	13.88	2016/328	3/4/2016	$30,000	0.52%	$30,156	$2,173
5-G	246.-2-5	Foster Hill Rd.	Avon	15.1	2015/1666	10/9/2015	$35,250	0.93%	$35,578	$2,356
5-H	249.-1-14.452	Hubert Watrus Rd.	Avon	15.2	2016/1823	10/19/2016	$38,000	−0.10%	$37,962	$2,498
5-I	215.-1-2.21	Cummings Rd.	Livonia	17.95	2015/1608	9/18/2015	$56,500	0.99%	$57,059	$3,179
			AVERAGE	**14.55**			**$35,187**		**$35,421**	**$2,434**
			MEDIAN	**15.1**			**$35,250**		**$35,578**	**$2,334**
Discount for Right-of-Way Access Based on Average Unit Prices										**66%**
Discount for Right-of-Way Access Based on Median Unit Prices										**66%**
Discount for Right-of-Way Access, Maximum Range										**83%**

Table 6. Onondaga County: Landlocked Residential Land										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						1/22/2013		**1%**		
Residential Land Sales with Landlocked Access										
6-A	65.1-01-25.0	2110 Valley Dr. Rear	Syracuse	1.38	5071/630	12/10/2008	$3,000	4.18%	$3,125	$2,265
6-B	75.-06-85.0	321 Corning Ave. W Rear	Syracuse	0.55	5114/599	11/1/2009	$385	3.26%	$398	$723
6-C	87.-08-25.0	226 Hubbell Ave. Rear	Syracuse	0.17	5227/282	1/22/2013	$500	0.00%	$500	$2,941
			AVERAGE	**0.7**			**$1,295**		**$1,341**	**$1,916**
			MEDIAN	**0.55**			**$500**		**$500**	**$909**
Residential Land Sales with Road Access										
6-D	79.-19-49.0	130 Fairfield Ave.	Syracuse	0.0909	5235/386	4/16/2013	$54,500	−0.23%	$54,375	$598,181
6-E	63.-02-09.0	315 Lafayette Rd.	Syracuse	1.3808	5311/585	10/16/2014	$35,000	−1.71%	$34,402	$24,914
6-F	100.-24-12.1	414 Gifford St.	Syracuse	0.2394	5436/444	7/14/2017	$7,500	−4.35%	$7,174	$29,966
6-G	100.-13-24.0	716 Otisco St.	Syracuse	0.1121	2017/44972	11/15/2017	$2,000	−4.68%	$1,906	$17,006
			AVERAGE	**0.4558**			**$24,750**		**$24,464**	**$53,673**
			MEDIAN	**0.1758**			**$21,250**		**$20,788**	**$120,910**
		AVERAGE WITHOUT 6-D		**0.5774**			**$14,833**		**$14,494**	**$25,101**
		MEDIAN WITHOUT 6-D		**0.2394**			**$7,500**		**$7,174**	**$31,328**
Discount for Landlocked Access Based on Average Unit Prices without 6-D										**92%**
Discount for Landlocked Access Based on Median Unit Prices without 6-D										**97%**
Discount for Landlocked Access, Maximum Range without 6-D										**98%**
Discount for Landlocked Access, Maximum Range with 6-D										**99.88%**

Table 7. Saratoga County: Landlocked Residential Land										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						2/8/2012		**1%**		
Residential Land Sales with Landlocked Access										
7-A	127.19-1-1	Parnil Dr. Rear	Wilton	5.08	2012/4717	2/8/2012	$6,000			$1,181
Residential Land Sales with Road Access										
7-B	127-1-9.1	164 Parkhurst	Wilton	5.04	2015/29728	9/30/2015	$88,000	-3.27%	$84,862	$16,838
7-C	141-3-30.111	129 Edie Rd.	Wilton	7.49	2013/44428	10/15/2013	$82,900	-1.67%	$81,517	$10,883
			AVERAGE	**6.265**			**$85,450**		**$83,190**	**$13,278**
			MEDIAN	**6.265**	**0.4558**		**$85,450**		**$83,190**	**$13,278**
Discount for Landlocked Access Based on Average Unit Prices										**91%**
Discount for Landlocked Access Based on Median Unit Prices										**91%**
Discount for Landlocked Access, Maximum Range										**93%**

Table 8. Steuben County: Landlocked Commercial Land										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						8/24/2015		**1%**		
Commercial Land Sale with Landlocked Access										
8-A	144.18-1-3	Off Route 54	Bath	1.03	42240	8/24/2015	$5,000		$5,000	$4,854
Commercial Land Sale with Road Access										
8-B	144.18-1-2	103 Route 54	Bath	0.46	42245	8/29/2015	$27,500	0%	$27,500	$59,783
Discount for Landlocked Access Based on Average Unit Prices										**92%**
Discount for Landlocked Access Based on Median Unit Prices										**92%**
Discount for Landlocked Access, Maximum Range										**92%**

Table 9. Fulton County: Landlocked Recreational Land										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						1/18/2008		**1%**		
Recreational Land Sale with Right-of-Way Access										
9-A	97.-2-22	Off Middle Sprite Rd.	Stratford	100.00	2018/48196	1/18/2008	$82,500	10%	$90,750	$908
Recreational Land Sale with Landlocked Access										
9-B	97.-2-22	Off Middle Sprite Rd.	Stratford	100.00	1096/15	12/28/2017	$25,000		$25,000	$250
Discount for Landlocked Access Based on Average Unit Prices										**72%**
Discount for Landlocked Access Based on Median Unit Prices										**72%**
Discount for Landlocked Access, Maximum Range										**72%**

Table 10. Saratoga County: Commercial/Residential Land with Right-of-Way Access										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						12/8/2017		**1%**		
Commercial/Residential Land Sales with Right-of-Way Access										
10-A	63.4-1-14	1502 Route 9 Rear	Moreau	22	2017/39610	12/8/2017	$40,000	0.00%	$40,000	$1,818
			AVERAGE	**22**			**$40,000**		**$40,000**	**$1,818**
			MEDIAN	**22**			**$40,000**		**$40,000**	**$1,818**
Commercial/Residential Land Sales with Road Access										
10-B (Res)	142.18-1-8.1	26 Kendrick Hill Rd.	Wilton	3.7	2015/37191	12/9/2015	$55,000	2.01%	$56,106	$15,164
10-C (Res)	142.18-1-2	23 Kendrick Hill Rd.	Wilton	3.28	2016/9562	3/25/2016	$45,000	1.71%	$45,770	$13,954
10-D (Comm)	127.-3-18	Route 9	Wilton	3	2017/25551	8/9/2017	$152,000	0.33%	$152,502	$50,834
10-E (Res)	63.4-4-33	459 Gan-sevoort Rd.	Moreau	3.89	2017/17384	6/2/2017	$40,000	0.52%	$40,208	$10,336
10-F (Res)	114.15-3-6.1	10 Buchanan Dr.	Wilton	6.44	2018/6163	2/16/2018	$77,500	-0.19%	$77,353	$12,011
10-G (Res)	128.5-3-41	12 Tawny Ter.	Wilton	3.03	2018/27132	7/26/2018	$60,000	-0.62%	$59,628	$19,679
			AVERAGE	**3.89**			**$71,583**		**$71,928**	**$18,490**
			MEDIAN	**3.49**			**$57,500**		**$57,867**	**$16,476**
		AVERAGE WITHOUT 10-D		**4.07**			**$55,500**		**$55,813**	**$14,229**
		MEDIAN WITHOUT 10-D		**3.7**			**$55,500**		**$56,106**	**$13,954**
Discount for Right-of-Way Access Based on Average Unit Prices										**90%**
Discount for Right-of-Way Access Based on Median Unit Prices										**89%**
Discount for Right-of-Way Access Based on Average Unit Prices Without 10-D										**87%**
Discount for Right-of-Way Access Based on Median Unit Prices Without 10-D										**87%**
Discount for Right-of-Way Access, Maximum Range without 10-D										**91%**
Discount for Right-of-Way Access, Maximum Range (Sale 10-D)										**96%**

Table 11. Chenango County: Agricultural Land with Right-of-Way Access										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						1/29/2016		**1%**		
Commercial/Residential Land Sales with Right-of-Way Access										
11-A	128.-1-9.5	Off County Road 2	German	23	2016/157	1/29/2016	$12,000	0.00%	$12,000	$522
			AVERAGE	**23**			**$12,000**		**$12,000**	**$522**
			MEDIAN	**23**			**$12,000**		**$12,000**	**$522**
Commercial/Residential Land Sales with Road Access										
11-B (Ag-Res)	190.-1-31	Collyer Rd.	Smithville	25.1	2015/457	3/16/2015	$45,000	0.87%	$45,392	$1,808
11-C (Ag-Res)	62.-1-14.3	State High-way 8	Columbus	17	2015/1417	9/4/2015	$27,500	0.40%	$27,610	$1,624
11-D (Ag-Res)	91.-1-20.4	George Peasley Rd.	Pharsalia	25.63	2015/1656	10/22/2015	$43,500	0.27%	$43,617	$1,702
11-E (Ag-Res)	217.-1-22.321	State High-way 12S	Oxford	23.41	2016/59	1/20/2016	$95,000	0.02%	$95,019	$4,059
11-F (Ag)	57.-2-38	Howard Hill Rd.	Smyrna	23	2016/1860	10/27/2016	$64,000	−0.74%	$63,526	$2,762
			AVERAGE	**22.83**			**$55,000**		**$55,033**	**$2,411**
			MEDIAN	**23.41**			**$45,000**		**$45,392**	**$1,922**
		AVERAGE WITHOUT 11-E		**22.68**			**$45,000**		**$55,813**	**14,229**
		MEDIAN WITHOUT 11-E		**24.05**			**$44,250**		**$56,106**	**$13,954**
Discount for Right-of-Way Access Based on Average Unit Prices										**78%**
Discount for Right-of-Way Access Based on Median Unit Prices										**73%**
Discount for Right-of-Way Access Based on Average Unit Prices without 11-E										**74%**
Discount for Right-of-Way Access Based on Median Unit Prices without 11-E										**70%**
Discount for Right-of-Way Access, Maximum Range without 11-E										**81%**
Discount for Right-of-Way Access, Maximum Range (Sale 11-E)										**87%**

Table 12. Wayne County: Landlocked Agricultural Land										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						3/30/2017		**1%**		
Agricultural Land Sales with Landlocked Access										
12-A	74113-00-507212	P/O 2752 Route 414	Galen	79.79	918/99480	3/30/2017	$128,500	0.00%	$128,500	$1,610
			AVERAGE	**79.79**			**$128,500**		**$128,500**	**$1,610**
			MEDIAN	**79.79**			**$128,500**		**$128,500**	**$1,610**
Agricultural Land Sales with Road Access										
12-B	70112-00-599639	Debusse Rd.	Lyons	34.8	918/95848	11/8/2016	$73,620	0.39%	$73,907	$2,124
12-C	74110-00-430772	Route 414 S	Galen	114.45	918/98534	2/22/2017	$326,000	0.10%	$326,326	$2,851
12-D	74110-00-877097	Smith Rd.	Galen	72.4	920/91500	5/30/2018	$250,000	-1.15%	$247,125	$3,413
12-E	72109-00-933966	Desmond Rd.	Galen	64.5	920/92967	7/20/2018	$192,500	-1.29%	$190,017	$2,946
			AVERAGE	**71.5375**			**$210,530**		**$209,344**	**$2,926**
			MEDIAN	**68.45**			**$221,250**		**$218,571**	**$3,193**
Discount for Landlocked Access Based on Average Unit Prices										**45%**
Discount for Landlocked Access Based on Median Unit Prices										**50%**
Discount for Landlocked Access, Maximum Range										**53%**

Table 13. Cayuga County: Physically Restricted Access Agricultural Land										
Sale #	**Tax Map #**	**Street**	**Town**	**Acres**	**Book/ Page**	**Sale Date**	**Sale Price**	**Time Adj.**	**Time Adjusted Price**	**Price Per Acre**
						9/2/2016		**1%**		
Agricultural Land Sales with Physically Restricted Access										
13-A	220.00-1-6.114	Main Rd.	Locke	45.44	1676/15	9/2/2016	$74,976	0.00%	$74,976	$1,650
			AVERAGE	**45.44**			**$74,976**		**$74,976**	**$1,650**
			MEDIAN	**45.44**			**$74,976**		**$74,976**	**$1,650**
Agricultural Land Sales with Road Access										
13-B	188.00-1-2.1	Jugg St.	Moravia	50	1616/5	2/5/2016	$100,000	0.57%	$100,570	$2,011
13-C	69.00-1-1.1	Haiti Rd.	Mentz	36.3	1624/154	4/15/2016	$54,000	0.38%	$54,205	$1,493
13-D	182.00-1-6.2	Dublin Hill Rd.	Ledyard	51.5	1634/184	7/15/2016	$280,000	0.13%	$280,364	$5,444
13-E	171.00-1-3.1	Sands Rd.	Ledyard	69.2	1637/233	8/11/2016	$400,000	0.06%	$400,240	$5,784
13-F	187.00-1-6.112	Rockefeller Rd.	Moravia	59.6	1651/320	11/28/2016	$125,000	−0.24%	$124,700	$2,092
13-G	226.00-1-16	Route 90	Genoa	72	1654/343	12/30/2016	$525,000	−0.32%	$523,320	$7,268
			AVERAGE	**56.4333**			**$247,333**		**$247,233**	**$4,381**
			MEDIAN	**55.55**			**$202,500**		**$124,700**	**$2,245**
Discount for Physically Restricted Access Based on Average Unit Prices										**62%**
Discount for Physically Restricted Access Based on Median Unit Prices										**26%**
Discount for Physically Restricted Access, Maximum Range										**77%**

Table 14. Summary of Discounts for Values of Restricted Access Land in Upstate New York					
				Discount from Access to Restricted Access	
Sale Group	**Location**	**Land Type**	**Access**	**Average $/Acre**	**Median $/Acre**
2	Cortland Co.	Commercial	Landlocked	78%	82%
6	Onondaga Co.	Residential	Landlocked	92%	97%
7	Saratoga Co.	Residential	Landlocked	91%	91%
8	Steuben Co.	Commercial	Landlocked	92%	92%
9	Fulton Co.	Recreational	Landlocked	72%	72%
12	Wayne Co.	Agricultural	Landlocked	45%	50%
1	Onondaga Co.	Commercial	Right-of-way	73%	84%
5	Chenango Co.	Recreational	Right-of-way	66%	66%
10	Saratoga Co.	Comm/Res	Right-of-way	90%	89%
11	Chenango Co.	Agricultural	Right-of-way	78%	73%
3	Wayne Co.	Industrial	No physical	52%	78%
4	Livingston Co.	Commercial	No physical	59%	31%
13	Cayuga Co.	Agricultural	**No physical**	62%	26%
			Overall Average, Landlocked	**78%**	**81%**
			Overall Median, Landlocked	**85%**	**87%**
			Overall Average, Right-of-Way	**77%**	**78%**
			Overall Median, Right-of-Way	**76%**	**79%**
			Overall Average, Physically Restricted	**58%**	**45%**
			Overall Median, Physically Restricted	**59%**	**31%**
			Overall Average, All Sales	**73%**	**72%**
			Overall Median, All Sales	**73%**	**78%**

Table 15. Summary of Restricted Access Discounts by Land Type in Upstate New York					
				Discount from Access to Restricted Access	
Sale Group	**Location**	**Land Type**	**Access**	**Average $/Acre**	**Median $/Acre**
11	Chenango Co.	Agricultural	Right-of-way	78%	73%
12	Wayne Co.	Agricultural	Landlocked	45%	50%
13	Cayuga Co.	Agricultural	No physical	62%	26%
6	Onondaga Co.	Residential	Landlocked	92%	97%
7	Saratoga Co.	Residential	Landlocked	91%	91%
5	Chenango Co.	Recreational	Right-of-way	66%	66%
9	Fulton Co.	Recreational	Landlocked	72%	72%
1	Onondaga Co.	Commercial	Right-of-way	73%	84%
2	Cortland Co.	Commercial	Landlocked	78%	82%
4	Livingston Co.	Commercial	No physical	59%	31%
8	Steuben Co.	Commercial	Landlocked	92%	92%
10	Saratoga Co.	Comm/Res	Right-of-way	90%	89%
3	Wayne Co.	Industrial	No physical	52%	78%

U.S. Market Net Return and Risk to Storing Corn and Soybeans, 1974–2017


By Carl Zulauf and Sanghyo Kim

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Abstract

Reemergence of crop surpluses has increased attention on storage as a marketing strategy. A few studies of storage returns have included both corn and soybeans, which are the largest U.S. acreage crops. Each study noted that returns differ, but none statistically tested the difference. This study statistically tests average net return and risk of net return from storing corn and soybeans at the U.S. market level. Average percent net return does not differ statistically for cash storage or for futures hedged storage of corn versus soybeans. Risk also does not differ statistically for cash storage but is statistically smaller for hedged storage of soybeans.

INTRODUCTION

With the return of surpluses to U.S. crop production, storage is a more important marketing strategy. Storage decisions are made by individual storage firms, but—as with any good or service—an aggregate storage market exists that reflects the cumulative decisions of the individual participants in the storage market. This study examines the average net return and risk of net return for the aggregate U.S. storage market for corn and soybeans, the two largest U.S. acreage crops. Understanding the aggregate storage market should help individual participants in the storage market make more informed storage decisions.

Only a few studies of storage returns have included both corn and soybeans. They are discussed in the following section. Each found that return to a given storage strategy differed for the two crops, but the different returns were not tested for statistical significance. Nevertheless, the consistent finding of different returns raises the question of whether returns to storing corn and soybeans differ.

In this article, we start with a review of studies that included returns to storing both corn and soybeans. Next, we address the selection of the analytical observation period, the calculation of net storage return, and the findings of this analysis. We end with a summary, conclusions, and implications.

LITERATURE REVIEW

Five studies were found that report returns to storing corn and soybeans. Paul (1970) examines return to bin space for corn, oats, rye, soybeans, and wheat deliverable in Chicago from 1952–1966. Frechette (1997) includes corn as a storage competitor to soybeans in the conceptual model and empirical analysis of the impact of Brazil's expanding soybean production on U.S. returns to storing soybeans from 1948–1991. Kastens and Dhuyvetter (1999) analyze performance of the cash-futures basis as a storage signal for corn, soybean, wheat, and sorghum at 23 Kansas locations from January 1982 to December 1998. Johnson (2017) reports on a study by Knorr for *Farm Futures* magazine that examines return to storing corn and soybeans in North Central Iowa from 1985–2016, usually from October to June. Bektemirova's (2014) thesis evaluates corn and soybean storage strategies from a grain elevator perspective between October 1 and June 30 using data for North Central Illinois from 1992–2012.

Paul reports average per bushel per year return to bin space of $0.016 for corn versus –$0.094 for soybeans. Frechette (1997, 1117) concludes that "corn storage is much less well rewarded by the market" since its Capital Asset Pricing Model (CAPM) beta coefficient is 0.78 versus 2.05 for soybeans. Kastens and Dhuyvetter (1999) find that the basis signal performs differently for corn and soybeans. For example, per bushel profit of unhedged storage increased $0.271 for soybeans but declined $0.174 for corn when storage decisions were based on deferred futures, a three-year historical basis, and commercial storage rates. Among the results Johnson (2017) presents graphically is that average per bushel net return to storing at commercial facilities from 1985–2016 is around $0.05 for corn but $0.60 for soybeans. Bektemirova (2014, 68) concludes that "results for soybean hedged and un-hedged storage strategies are dramatically different from corn results." None of these studies report statistical tests of the difference in corn and soybean storage returns.

PROCEDURES

Analysis Period

The analysis period for this study begins with the 1974 market year and ends with the 2017 market year. The ending point was the last market year with complete data when the analysis was started. The beginning year reflects the increase in price variability after 1973 (Kenyon, Jones, and McGuirk, 1993). The increase coincided with increasing demand, particularly from the Soviet Union, and declining stocks, especially U.S. public stocks.

In response to changing market conditions in the early 1970s, the Agriculture and Consumer Protection Act of 1973 enacted changes that initiated a policy evolution toward greater price flexibility (Coppess, 2018; Orden, Paarlberg, and Roe, 1999; Zulauf and Orden, 2016). In particular, high fixed price supports that put a floor under market price were gradually replaced by programs that paid farms when market price was below a Congressionally set target price. After a return to high public stocks in the early and mid-1980s, Congress also began to reduce the role of public stocks starting with the Food Security Act of 1985. Congress eventually eliminated most public stocks programs, as well as another excess supply program—annual land set asides—in the Federal Agriculture Improvement and Reform Act of 1996. (All farm bills are available from the National Agricultural Law Center.)

The analysis period thus covers a variety of market and government policy situations, but with increasing reliance on private storage. The variety should increase the power and robustness of the analysis, but it also raises the issue of whether the U.S. storage market for corn and soybeans has changed over the analysis period.

Today, almost all U.S. stocks of corn and soybeans are held by private storage firms. A key, but not the only, factor in the evolution away from public stocks was the cost, particularly when cost included the displacement of private stocks by public stocks. Kim and Zulauf (2019) provide a detailed discussion of this displacement, including other literature citations. They develop a conceptual model using a call option associated with the release of public stocks. The model reveals that the degree to which public stocks crowd out private stocks depends on the elasticity of demand. It thus varies by commodity and is likely to be highest for commodities with the most inelastic demand. An empirical analysis using data from U.S. public stocks programs confirms this and other insights from the conceptual model regarding private stock displacement.

U.S. share of world soybean production has also declined notably, from 75% in 1974 to 34% in 2017, using data from the United States Department of Agriculture's (USDA's) Production, Supply, and Distribution database. The large decline has underpinned an argument that the incentive to store soybeans in the United States would decrease, especially after March when Brazilian production becomes available for consumption (Frechette, 1997; Bektemirova, 2014). The U.S. share of world corn production has declined, but only from 40% to 35% since 1973.

To investigate the possibility that return and risk in the U.S. corn and soybean storage market has changed since 1974, a sensitivity analysis is conducted. Specifically, net return and risk are calculated for the first and second half of the analysis period: 1974–1995 and 1996–2017. Splitting an observation period in half is a common sensitivity test. The halfway split in this analysis (1995 market year) also coincides with the major changes in U.S. farm policy enacted in the 1996 U.S. Farm Bill. Thus, splitting the 1974–2017 analysis period in half should provide insights into whether return and risk in storing U.S. corn and soybeans have changed since 1974.

Calculation of Storage Return

The focus of this research is the base market level net return and risk to storing U.S. corn and soybeans. Return and risk are thus examined for the two most common types of storage: cash storage and storage hedged with a short futures position that is offset when the stored crop is sold in the cash market. More dynamic storage strategies, such as rolling hedged storage to a more distant futures contract until a cash sale is made, are not examined.

The cash price used in this analysis is the average monthly price paid to U.S. farmers by first handlers as reported by the USDA National Agricultural Statistics Service (NASS). A statistical advantage of using national average prices is that they have less statistical noise, which raises the power of statistical tests (Siaplay et al., 2012).

Storage starts in October, the month with the lowest average cash corn and soybean price. Since 1974, the U.S. price of corn as reported by USDA NASS averaged $2.76 per bushel in October. The next lowest month is November, also at $2.76. For soybeans, the October price averaged $6.94, with November next lowest at $7.05.

The storage hedge is placed in the Chicago July futures contract. July futures is the latest, same-month futures contract traded for both corn and soybeans in their market year, which begins September 1. To avoid pricing anomalies that can arise during a futures delivery month, the last storage month is June. Average settlement price of the July futures contract is calculated for each month from October through June using prices from Barchart.com.

Per bushel gross return to cash storage is calculated monthly as average U.S. cash price for the end-of-storage-period month (November through June) minus the average cash price for October. Per bushel gross return for hedged storage is the change in cash price plus the associated change in futures price, or equivalently the change in cash-futures basis, over the storage period.

Net return to storage equals gross return minus physical storage cost to keep the crop in usable condition, interest opportunity cost, and brokerage fee plus liquidity cost for the futures trade. Insurance for physical loss of the stored crop is also a storage cost but—due to its small size for grains and oilseeds—is often not included, a practice adopted in this study.

Physical storage cost is from the USDA Commodity Credit Corporation (CCC) through the 2005 market year. Between 2005 and 2006, the CCC-reported storage rate jumped from $0.35 to $0.875 per bushel per year for corn and from $0.25 to $0.85 per bushel per year for soybeans. Based on the material received from CCC, it is not clear how their methods changed nor why a change was made. Given the size of the jump, storage rates were collected from an Ohio country and terminal elevator. The storage rate was $0.48 for both elevators and both crops in 2005 and 2006. Thus, beginning with the 2006 market year, physical storage cost is from an Ohio country elevator, cross-checked with another Ohio elevator. Because of the change in the data source for physical storage rate, the physical storage rate used in this study was compared with the rates used by other studies cited in the literature review when possible to make such a comparison. The rates used in this study are nearly identical to the physical storage rates used by Kastens and Dhuyvetter (1999) and the commercial storage rates used by Johnson (2017).

Over the 1974–2017 analysis period, physical storage cost in this study averages $0.37 per bushel per year for both corn and soybeans, with a range of $0.16 (1974) to $0.60 (2011–2017). As a point of observation, it is common to assume in storage studies that cost of storage is less for on-farm storage than for commercial off-farm storage. For example, Johnson (2017, 1) reports that “Knorr used a handling and storage costs [sic] of $0.01 to $0.02 per bushel per month for on-farm storage and $0.025 to $0.05 per bushel per month for commercial storage” over the 32 years in his study.

Deciding to store means foregoing the opportunity to use the cash receipts from selling at harvest. Opportunity cost in this study is measured using the average secondary market six-month U.S. Treasury bill rate for October and November. Six months is the Treasury bill maturity length closest to the eight-month October to June storage period (Federal Reserve Bank of St. Louis, 2018). The interest rate averages 4.78%, ranging from 0.05% (2014) to 13.82% (1981).

The brokerage fee is $50 for a round trip buy and sell of a futures contract, based on inquiries of brokers. The liquidity cost of trading futures contracts arises since trades are not instantaneously executed. The price at which a futures trade is executed thus likely differs from the price at which the trade is placed. Based on Brorsen (1989) and Thompson and Waller (1987), liquidity cost is $25 per futures trade made before February 1 and $12.50 thereafter. Liquidity cost is lower after February 1 because trading volume increases as contract maturity approaches. Per bushel futures trading cost is obtained by dividing by 5,000 bushels, which is the size of a corn and soybean futures contract.

FINDINGS

Since 1974, average net return, expressed as a percent of the October harvest price, is higher for cash storage of soybeans than cash storage of corn for all eight storage periods (Figure 1). Average net return to hedged storage of soybeans and corn is closer and often nearly identical.

As measured by standard deviation of net return across years, risk of net return is close to identical for cash storage of corn and soybeans at the same storage length (Figure 2). Risk of net return to hedged storage is higher for corn than soybeans at each storage length.

The most common methodology for testing if differences are statistically significant is the t-test for means and F-test for variances. Both assume a normal distribution. The Shapiro-Wilk test for normality is not rejected for 11 of the 16 difference series (two strategies at eight storage lengths). Given the preponderance of evidence for normality, the t-test and F-test are used to test for statistically significant differences in net return to storage and storage risk.

At the commonly used 95% confidence level and using a paired t-test, average percent net return to storing corn and soybeans differs statistically for only three of the 16 storage combinations. Each exception is a higher net return to storing soybeans than corn. The three exceptions are October to November cash and hedged storage and October to June cash storage.

Using the F-test, net return risk does not differ statistically, with 95% confidence between cash storage of corn and soybeans for any storage period. In contrast, net return risk is higher for hedged storage of corn than hedged storage of soybeans for all storage lengths.

Although the focus of this analysis is on comparing net storage return and risk for corn versus soybeans at the U.S. market level, it is important to note that return net of commercial off-farm storage cost does not differ statistically from zero, with 95% confidence for cash and hedged storage of corn and soybeans at any storage length except for corn that is hedge stored from October to November. Consistent with the literature (Bektemirova, 2014; Kastens and Dhuyvetter, 1999), net return risk is smaller for hedged than cash storage, with 95% statistical confidence for both corn and soybeans at all storage lengths except for corn stored from October to January.

Turning to the subperiod sensitivity analysis, no statistically significant difference with 95% confidence is found for average net return to storing corn versus soybeans during 1974–1995, either with respect to each other or from zero at any storage length (Table 1). During 1996–2017, net return to cash storage is significantly higher for soybeans than corn, with 95% confidence for October to November, October to May, and October to June storage. Net return is significantly greater than zero for cash soybean storage from October to January, October to May, and October to June but is significantly less than zero for hedged soybean storage from October to March and October to April. In both subperiods, net return risk does not differ statistically between cash storage of corn and cash storage of soybeans. In contrast, risk of net return is higher for hedged storage of corn than for hedged storage of soybeans at six of the eight storage lengths in the first subperiod and at five of the eight storage lengths in the second subperiod. While some differences are found across the two subperiods, the preponderance of evidence is that, with regard to average net return and net return risk, the U.S. storage market for corn and the U.S. storage market for soybeans differ little between the two subperiods.

As a group, the subperiod findings imply that the U.S. storage market has provided no incentive for firms to alter storage of soybeans versus corn over time. Consistent with this implication, soybean's share of U.S. corn plus soybean stocks exhibits little to no time trend in each of the quarterly U.S. stock reports (Figure 3). A linear time trend explains none, 6%, 9%, and 13% of year-to-year variation in soybean share for, respectively, the December, June, March, and September stock reports. Only the September time trend is significant, with 95% confidence—and its significance disappears if the first three years (1974–1976) are excluded.

SUMMARY, CONCLUSIONS, AND IMPLICATIONS

In general, average net return is found to be similar for the U.S. corn and soybean storage markets from 1974–2017. This finding holds for cash and hedged storage. Assuming off-farm commercial physical storage costs, net storage return is found to not differ from zero for corn and soybeans. On the one hand, the finding of similar net returns to storing corn and soybeans is not surprising since they compete for the same storage bin space. On the other hand, this finding is surprising since return to storing U.S. soybeans has not been impacted by the large increase in soybean production outside the United States. Further study of this topic may provide insights into the relative role of domestic and international factors in determining returns to U.S. storage of crops.

Net return risk is similar for corn and soybean cash storage. The findings of similar average net return and similar net return risk for cash storage of corn and soybeans suggest that at the U.S. market level there is no routine incentive to store one crop over the other when using cash storage.

Consistent with the literature, net return risk is lower for hedged than cash storage of both corn and soybeans. Moreover, net return risk is lower for hedged storage of soybeans than for hedged storage of corn, with 95% statistical confidence. Thus, at the U.S. market level, this study suggests hedged storage of soybeans is more advantageous than hedged storage of corn due to its lower risk.

Individual storage agents make storage decisions in local storage markets within the context of the broader national storage market. Findings of this study of the U.S. corn and soybean storage markets are thus best utilized by individual storage agents when combined with a similar analysis of their local storage market. A combined analysis offers the potential to identify situations when deviations from the normal relationship between local and national market returns to storage may be used to enhance identification of local storage profits and thus improve local storage decision-making. For example, instead of examining the local basis by itself, examining the relationship between the local market basis and national market basis may provide local storage agents with additional insights into when local storage will be profitable.

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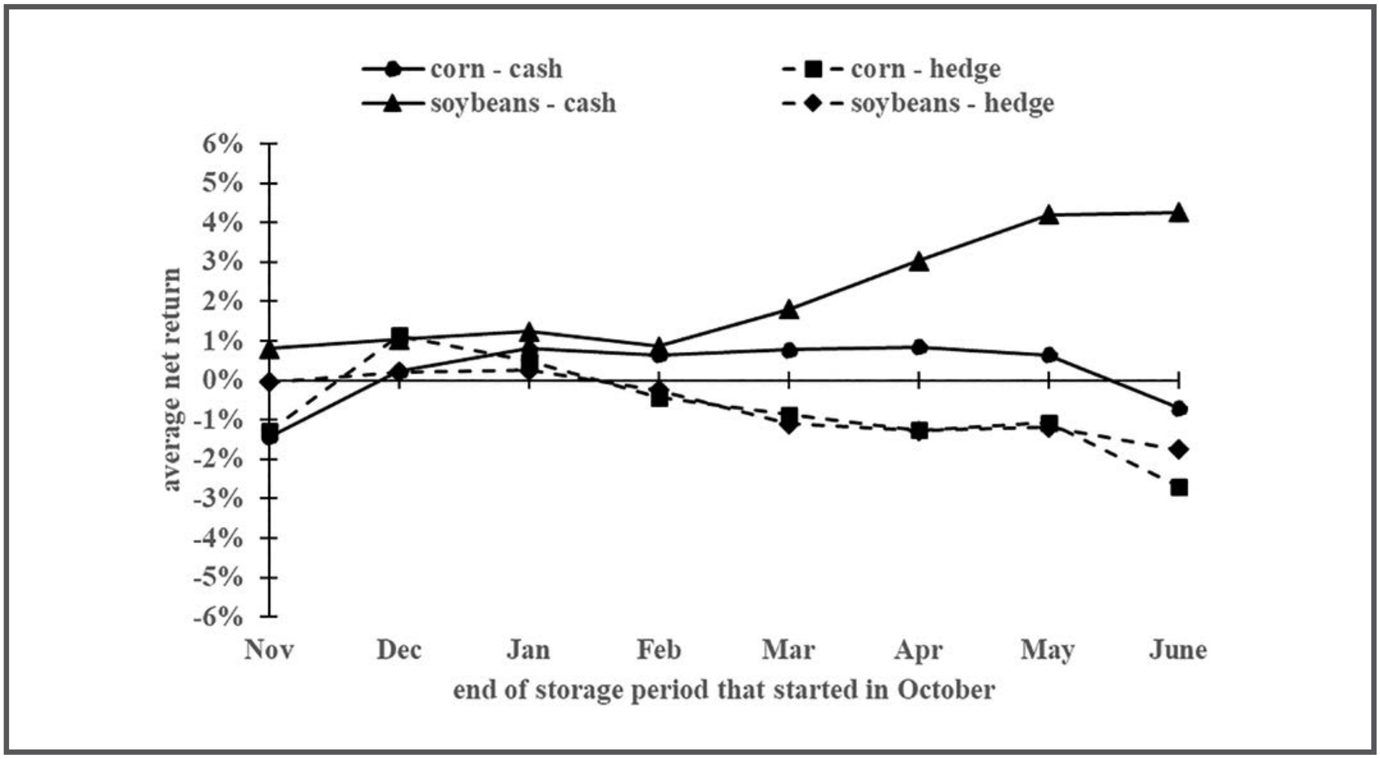

Figure 1. Net Return, Cash and Hedged Storage, U.S. Corn and Soybeans, 1974–2017 (Source: Original calculations; data from USDA NASS Quick Stats, USDA CCC, an Ohio country elevator, the Federal Reserve Bank of St. Louis's Federal Reserve Economic Data, and Barchart.com)

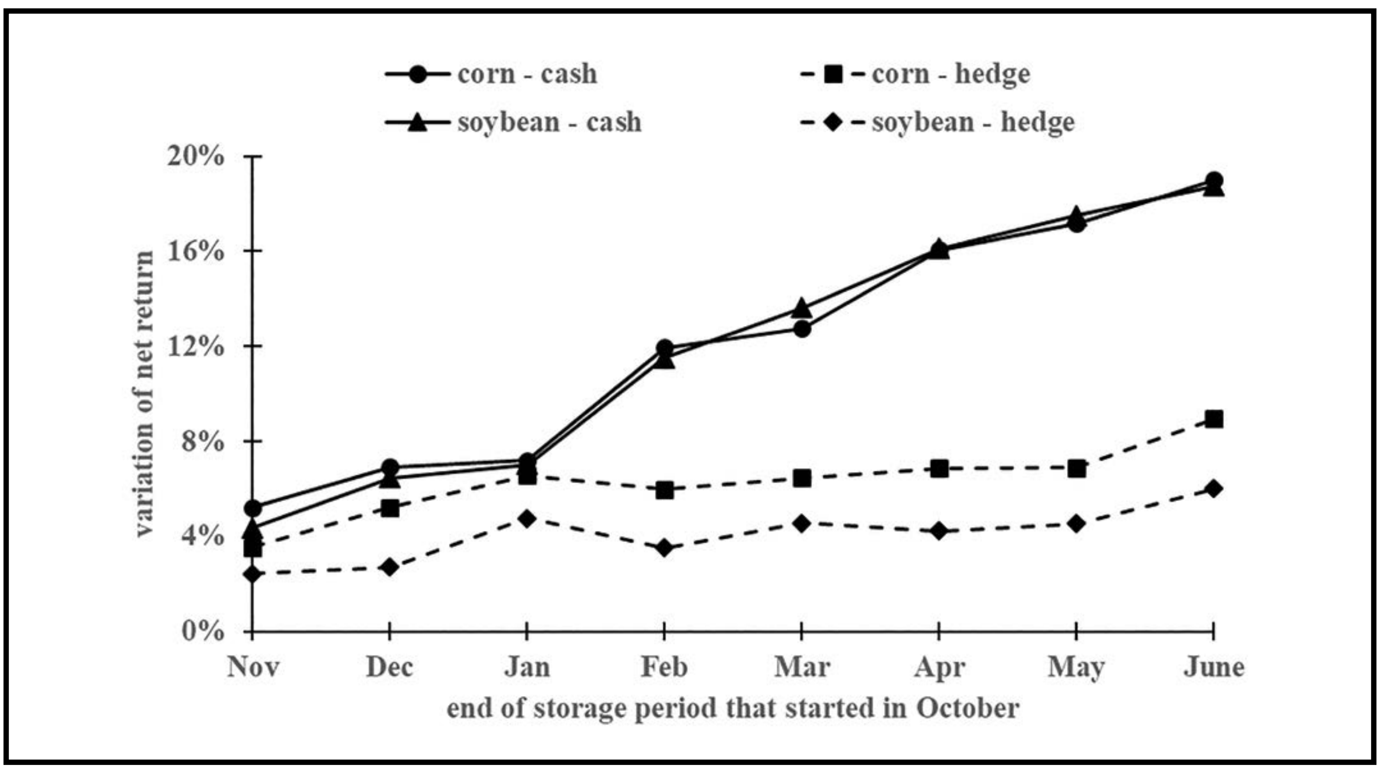

Figure 2. Risk of Net Return, Cash and Hedged Storage, U.S. Corn and Soybeans, 1974–2017 (Source: Original calculations; data from USDA NASS Quick Stats, USDA CCC, an Ohio country elevator, the Federal Reserve Bank of St. Louis's Federal Reserve Economic Data, and Barchart.com). Note: Risk equals standard deviation of annual net storage return from harvest to indicated month.

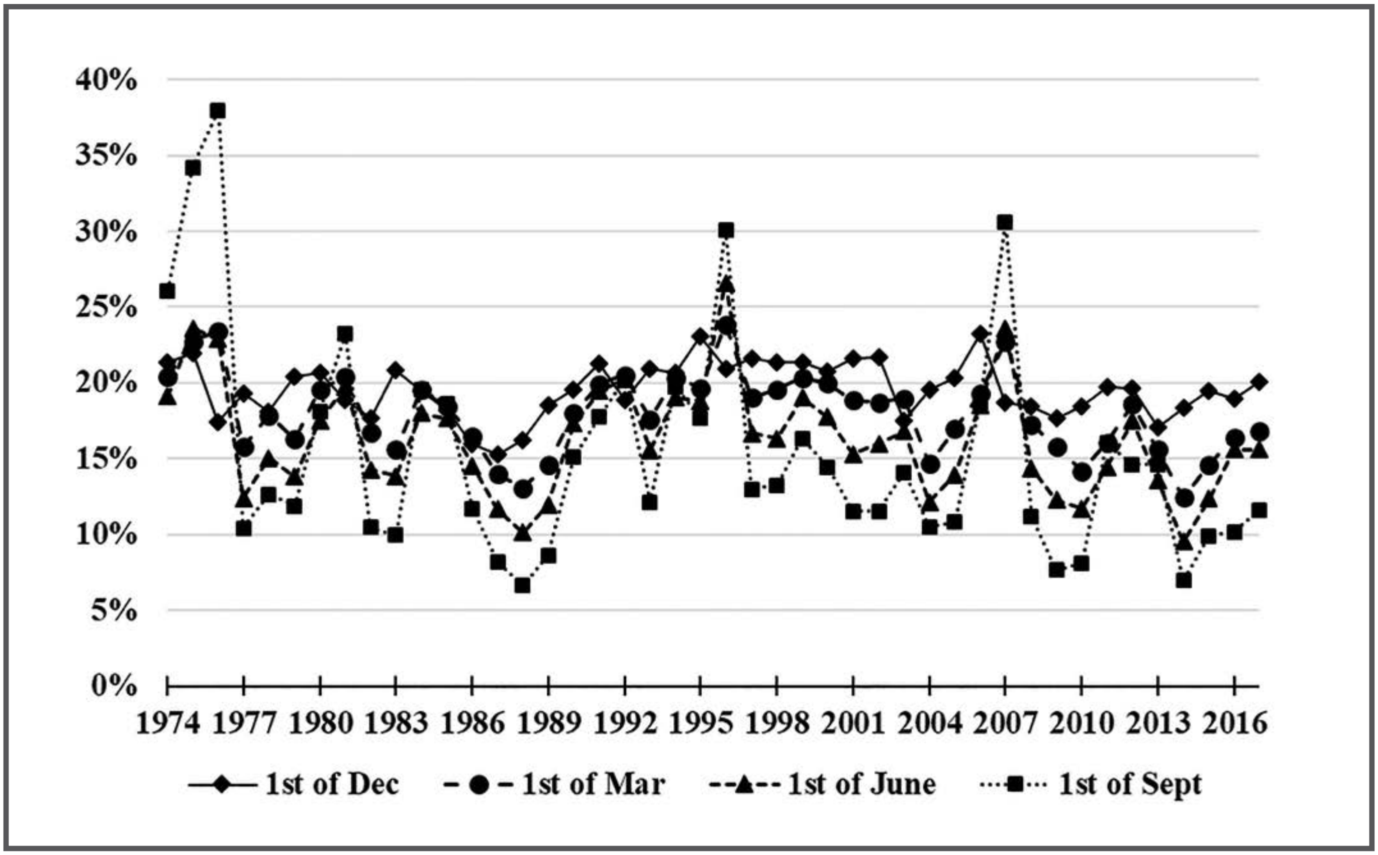

Figure 3. Soybean Stocks as a Share of Corn Plus Soybean Stocks, U.S. March, June, September, and December Stock Report, 1974–2017 (Source: Original calculations; data from USDA NASS Quick Stats and USDA NASS Grain Stocks)

Table 1. Net Return and Risk of Net Return, Cash and Hedged Storage, U.S. Corn and Soybeans, 1974–1995 and 1996–2017

	End of Storage Period that Started in October							
	Nov.	Dec.	Jan.	Feb.	March	April	May	June
Net Return, 1975–1995								
Cash Storage								
Corn	-1.8%	-0.1%	0.1%	-0.6%	-0.4%	0.0%	0.6%	0.4%
Soybeans	0.0%	-0.3%	-0.3%	-2.0%	-1.1%	0.2%	1.0%	0.8%
Hedged Storage								
Corn	-1.4%	1.6%	1.3%	0.8%	0.6%	-0.7%	-0.7%	-2.8%
Soybeans	-0.1%	0.6%	1.4%	0.8%	0.1%	-0.6%	-0.7%	-1.0%
Net Return, 1996–2017								
Cash Storage								
Corn	-1.0%*	0.5%	1.5%	1.9%	2.0%	1.6%	0.7%*	-1.8%*
Soybeans	1.75%	2.3%	2.8%#	3.7%	4.7%	5.9%	7.4%*,#	7.7%*,#
Hedged Storage								
Corn	-1.2%	0.7%	-0.3%	-1.6%	-2.4%	-1.9%	-1.5%	-2.6%
Soybeans	0.0%	-0.2%	-0.9%	-1.3%	-2.3%#	-2.0%#	-1.7%	-2.5%
Risk, 1975–1995								
Cash Storage								
Corn	5.9%	7.3%	7.4%	10.5%	12.1%	14.7%	16.2%	18.8%
Soybeans	4.4%	6.5%	7.0%	11.5%	13.6%	16.1%	17.5%	18.7%
Hedged Storage								
Corn	3.5%*	5.2%*	5.5%*	5.0%*	5.0%	5.3%*	6.4%*	7.2%
Soybeans	2.4%*	2.7%*	4.8%*	3.5%*	4.6%	4.3%*	4.5%*	6.0%
Risk, 1996–2017								
Cash Storage								
Corn	4.5%	6.7%	7.1%	13.4%	13.5%	17.7%	18.5%	19.6%
Soybeans	4.4%	5.8%	5.2%	11.7%	13.4%	15.2%	15.3%	16.7%
Hedged Storage								
Corn	3.6%	5.3%*	7.5%	6.7%*	7.5%*	8.2%*	7.5%	10.6%*
Soybeans	2.6%	2.8%*	5.7%	3.8%*	4.6%*	4.7%*	5.4%	6.5%*

*Net return or risk differs for corn vs. soybeans, with 95% statistical confidence.

#Net return differs from zero, with 95% statistical confidence.

Note: Risk is standard deviation of annual net storage return from harvest to indicated month.

Source: Original calculations; data from USDA NASS Quick Stats, USDA CCC, an Ohio country elevator, the Federal Reserve Bank of St. Louis's Federal Reserve Economic Data, and Barchart.com.

Decision-Making: How Involved Are Our Producers and Hired Managers?

By Maria Bampasidou and Whitney McKinzie

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Abstract

This study presents information on the involvement of U.S. producers in farm management decision-making by age profile. We use data from the 2017 Census of Agriculture, the first Census that collected information on decision-making. Moreover, it is the first time the Census accounted for up to four people per farming operation, which allows for a better assessment of shared decision-making at the farm level. Further, we turn our attention to young producers and hired managers and highlight the importance of early involvement in decision-making for the sustainability and growth of the agricultural sector, particularly in transition planning considering the aging of the U.S. producer population.

INTRODUCTION

Effective and efficient decision-making is important in business planning and goal setting and contributes to the success of an operation, shielding it from the risk and uncertainty commonly experienced in farming. It is therefore imperative that successful producers are good decision-makers. Producers mainly focus on day-to-day decisions, short-term tasks, and time-sensitive situations. Yet, in every operation, there are sets of decisions that reflect intermediate-term plans and goals such as investment in machinery, asset ownership, and land acquisition—as well as decisions that have a larger impact in the long run related to succession and transition planning. Still, short-term, intermediate-term, and long-term decisions are interconnected. For example, day-to-day farm management problems are reflected in costs or revenues, which are linked to the financial position of an operation (intermediate-term) (Doye, 2018). Moreover, financial management is a key component of the financial health of the operation, which may affect estate planning and succession planning decisions (long-term).

The relationship between the number of people involved in decision-making and respective farm management decisions has not been thoroughly explored, largely because of lack of individual level data on these variables.[1] For instance, agricultural surveys, such as the national agricultural censuses, tend to collect information from one operation and one representative, mostly the principal operator or the head of the household (Twyman, Useche, and Deere, 2015; Mold, 2019). This practice simplifies the analysis at the farm level since in the majority of cases the principal operator is the landowner and farm manager and therefore the one who makes decisions. However, it conceals important information on the dynamics of the farm household, the tasks each member is responsible for, and their involvement in decision-making. Thus, an important component is overlooked because multiple people, of perhaps different generations, own different assets in an operation and manage different aspects of it. Their decisions will impact the future of the family business and are important for all family members (Hofstrand, 2007). Therefore, we need to address the following question: "How representative is the information presented in these surveys, considering that perhaps out of respect or cultural norms in some cases, the principal operator is defined as the elder of the household and is the person who completes them?"

This study presents information on the involvement of U.S. producers in decision-making using data from the 2017 Census of Agriculture, hereafter referred to as the 2017 Ag Census. The 2017 Ag Census collected information for the first time on decision-making related to farm management[2] and on multiple individual operators in a farm. Our study shows the concentration of producers by age in five different categories of decision-making, ranging from short-term day-to-day decisions to estate planning and succession planning—what we classify as long-term decisions. This paper focuses on disaggregating the U.S. producer population; it accounts for a larger information set and is different from other studies that present results using principal operators only.

Special focus is given to presenting data and information on young producers. The 2012 Ag Census revealed demographic challenges in agriculture, with the average farmer being 56.3 years old and 58.3 years old for principal operators (Census of Agriculture, 2012). Agricultural stakeholders stressed the need of a young cohort of farmers to be able to sustain the farm sector as the current generation of farmers retires (Menker, 2016). The results from the 2017 Ag Census showed that the age-increasing trend continues, with the average age of an operator being 57.5 years old and the average age of a primary operator being 59.4 years of age.[3] Considering that the majority of the U.S. farm operations are sole proprietorships and that family members are working on the farm, it is important to identify the younger generation of farmers and examine their involvement in decision-making. The last objective of this study is to analyze information about hired managers' involvement in decision-making, documenting their contribution to the farm sector.

The remainder of the paper is organized as follows: In the next section, we provide the context of our analysis by documenting changes in the 2017 Ag Census data collection and the questions on decision-making. We comment on the distinction of decisions based on the time horizon. In the subsequent section, we present the results of involvement in decision-making by age group, followed by an analysis of the young producers and hired managers. We also provide a discussion of the results. The last section concludes and comments on areas of further investigation.

STUDY CONTEXT

The 2017 Ag Census revised the approach of collecting information on demographics for U.S. producers. Since 2002, the questionnaire allowed one person to be identified as the principal operator, and data was collected for up to three operators—the so-called primary operators. This limited the analysis in terms of contribution in farm duties, farm management, and decision-making. The 2017 Ag Census allowed up to four people to provide information. The wording changed from "up to three primary operators of this operation" to "up to four individuals who were involved in the decisions for this operation." The 2017 Ag Census also identified primary operators, which is the equivalent of the principal operators in the 2012 Ag Census.

The question on specific decisions collected information on (i) day-to-day decisions, (ii) land use and/or crop decisions, (iii) livestock decisions, (iv) record keeping and/or financial management, and (v) estate planning or succession planning. We categorize decisions by the length of time it takes to observe the outcome of the decision. We consider the day-to-day decisions as short-term decisions that require immediate attention, and we expect the majority of responses to be in this category.

Decisions regarding land use and crop decisions include planting and crop spraying, which lends more to the area of production management. Livestock decisions include purchases, sales, breeding, and pasturing, which is a combination of production practices and marketing. The involvement in these decisions depends on the farm operation. Decisions on crop production and livestock tend to be made yearly and may take a year or less to be implemented and evaluated. Financial management and record keeping are essential decisions for all farm enterprises; therefore, we expect to see a higher response in this area. Record keeping activities happen throughout the year, and financial statements reflect the accounting year of the operation. We consider land use, livestock, and financial decisions as intermediate-term decisions. Lastly, estate planning and succession planning are decisions that take longer to be made and implemented. We expect to see a higher concentration of older producers actively involved in estate planning and succession planning.

RESULTS AND DISCUSSION

Decision-making involvement by age group is shown in Figure 1; we also comment on potential statistically significant differences between age groups and the total U.S. producer population within a type of decision. The y-axis lists the types of decisions and the x-axis presents the percentage of producers engaged in the respective decision type. We used the 2017 Ag Census classification on age groups, namely under 25, 25–34, 35–44, 45–54, 55–64, 65–74, and 75 years and over. We did not group together any age profiles. This allowed us to get a better understanding of decision involvement by age cohorts within the farm. The first set presents information on the total number of U.S. producers and is used for benchmark analysis. The complexity of farm operations and their management is reinforced considering that multiple people are actively engaged in farm operations, which increases the opportunity for shared responsibility and decision-making. As expected, the majority of the U.S. producers partake in day-to-day decision-making. Land use, financial management, and livestock decisions follow, and estate planning or succession planning decisions are placed last.

The analysis by age group showed a higher concentration in day-to-day decision-making for all age groups, hence prioritizing short-term decisions and tasks that require immediate attention. Financial management and record keeping is another category of decisions where we observed a high concentration of responses for all age groups, except for producers under the age of 25. In terms of long-term decision-making, less than 50% of all producers under the age of 44 are involved in estate or succession planning. Our analysis showed that a higher concentration of producers above the age of 65 are more involved in estate or succession planning relative to the younger age cohorts. This could potentially be explained by the fact that producers above the age of 65 are closer to retirement. Considering the amount of time it takes to implement practices related to estate or succession planning, it is essential to involve producers of all ages in the long-term decision-making process.

We furthered our analysis by constructing two subgroups, namely producers younger than 35 years old and producers age 35 years old or older, to examine age dynamics. We examined potential differences in decision-making by category of decisions. Table 1 presents information on the total number of producers in each subgroup, the number of producers involved in the respective decision, and proportion scores. The two groups vary significantly in all categories of decision-making.

Young Producers

Figure 2 presents information on the concentration of young producers as part of the total U.S. producers by county. According to the United States Department of Agriculture (USDA), a young producer is someone who is "35 years of age or younger" (Census of Agriculture, 2017). The 2017 Ag Census reported 321,261 (205,110 male and 116,151 female) young producers in the United States. This cohort of farmers comprises 9.4% of the total U.S. producer population and operates 240,121 farms, with an average total value of agricultural production of $273,522. The five states with the lowest concentration of young producers are Texas (6.9%), New Jersey (6.9%), New Mexico (7.0%), Hawaii (7.0%), and Florida (7.1%). The five states with the highest concentration of young producers are Pennsylvania (13.9%), North Dakota (12.4%), Indiana (12.3%), Nebraska (11.9%), and South Dakota (11.7%). These five states are above the 9.4% U.S. average.

The majority of young producers are involved in short-term day-to-day decisions (Figure 3). Production decisions related to land use and/or crop decisions is the second category with the most responses. Financial management and record keeping is the third category, followed by livestock decisions. The results for principal operators follow the same pattern. Young producers are least involved in long-term decisions, captured by estate planning and succession planning. Only about 42% of young producers are reported to participate in this set of decisions. The results for principal operators are slightly better; 50% of the total young principal producers partake in estate and succession planning.

To tackle potential differences by type and location of operation, we investigated decision-making of young producers based on the 10 USDA production regions: Pacific, Mountain, Southern Plains, Northern Plains, Lake States, Corn Belt, Delta States, Southeast, Appalachian, and Northeast. Our results can be found in Table 2. The Corn Belt region had the highest concentration of young producers making decisions in each decision category, with approximately 20% to 22% in each decision category. Both the Appalachian and Southern Plains regions consisted of relatively high percentages of young producers making decisions in each decision category, with roughly 12% to 13% for both regions.

Hired Managers

There is an increasing trend on relying on hired managers to supervise farming operations, so it is important to see the level of their involvement in decision-making. The USDA defines a hired manager as a person who receives a wage to supervise daily operations of a farming establishment (Census of Agriculture, 2017). A total of 158,298 (119,488 male and 38,810 female) hired managers were reported in the 2017 Ag Census, 45% of whom are primary producers. The involvement of hired managers in decision-making is presented in Figure 4. Day-to-day decisions is the category with the most responses, followed by record keeping and financial management. This may be because their primary job is to monitor the operation and ensure that time-sensitive tasks are completed and immediate goals are reached. This potentially explains why the estate or succession planning category has such a low number of responses.

CONCLUDING REMARKS AND FURTHER RESEARCH

This study presented information on the U.S. producer involvement in decision-making by age group in an attempt to investigate decisions in managing different aspects of farm operations. Our results are based on data collected from the 2017 Ag Census. We reported on the maximum potential number of respondents per operation rather than solely on principal and primary operators, to better capture multiple generations working at the farm and engaged in decision-making. We examined their involvement in terms of the time it takes for a decision to be made, implemented, and evaluated. Short-term decisions are the focus of U.S. producers in every age group. As producers become older, their involvement in long-term decisions—in our context estate planning and succession planning—increases.

Looking closely at the subgroup of young producers, which includes people younger than 35 years old, we observed a concentration on short-term and intermediate-term decisions. We cannot interpret our results as a lack of interest in estate planning or succession planning based on our data. We note that as the average U.S. producer ages, it is imperative to include young producers in discussions regarding transition and succession planning. Successful transition to the next generation relates to challenges with inadequate estate planning and retirement planning (Ferrell, Jones, and Hobbs, 2015; Kirkpatrick, 2013). For hired managers, our results can be interpreted in terms of their work specification and role, which prioritizes day-to-day decisions and financial management.

This preliminary analysis revealed some areas that need further attention. The content of the questions, although it allows for a first-step analysis, may be limiting due to the combination of lesser decisions listed in a category—particularly for the land use and livestock decisions category. Too many options provided may increase the response rate but may also create confusion on the interpretation of the results. Moreover, other categories can be included related to marketing and human risk management, as well as technology adoption. Decisions at the farm level may have an impact outside of the geographic boundaries of the farm operation (Edwards-Jones, 2006).

Another point that needs attention is how to identify peoples' roles and how that may affect survey responses. The new format allows more people to be counted, but we cannot eliminate the individual factor of who completes the survey. Regarding decision-making, we note that this is self-reported data and that there may be limitations on how respondents evaluate their involvement in the respective decisions. Another interesting future investigation is the disaggregation of data by gender, which we believe would provide results that are more informative. For example, women are reported to be more involved in financial management and record keeping versus men, who tend to focus on production decisions.

We note here that our analysis is not exhaustive but works as a first step in this direction. The data on decision-making will provide important information when combined with farm characteristics such as size of operation and economic class, as well as farmer characteristics such as experience. Analysis at the farm level by identifying multiple operators in farming operations will also provide a better understanding of shared and joint management and decision-making. That, in turn, will yield a better understanding of the dynamics of farm households and more targeted USDA and extension programs on young farmers, women, and new and beginning farmers. Better statistics will lead to better policy making.

At the next level, it will be interesting to see applications of this work on understanding the process and consequences of decision-making. This strand of literature has been well-established in documenting farmers' behavior with respect to technology adoption, adoption of credit, and environmental practices, as well as behaviors and personality traits (Willock et al., 1999a; Willock et al., 1999b).

FOOTNOTES

[1] There is a strand of literature that looks at women's involvement in decision-making and participation in agricultural production, highlighting the bias toward indicating men as the decision-makers (Udry, 1996; Peterman et al., 2011; Twyman, Useche, and Deere, 2015). This literature is mainly focusing on developing countries. In its newest *Highlights* series, "Farm Producers," the 2017 Ag Census provided information on the involvement in decision-making for women and men operators. We comment that this is not the focus of our analysis, although some elements can apply to a gendered analysis instead of an age group analysis.

[2] The Census of Agriculture collects information on parameters related to farm management, such as labor allocation (e.g., days worked off-farm). The 2017 Ag Census has a separate question on farm management decision-making in Section 7 on Personal Characteristics.

[3] The principal operators in the 2012 Ag Census are equivalent to the primary operator in the 2017 Ag Census.

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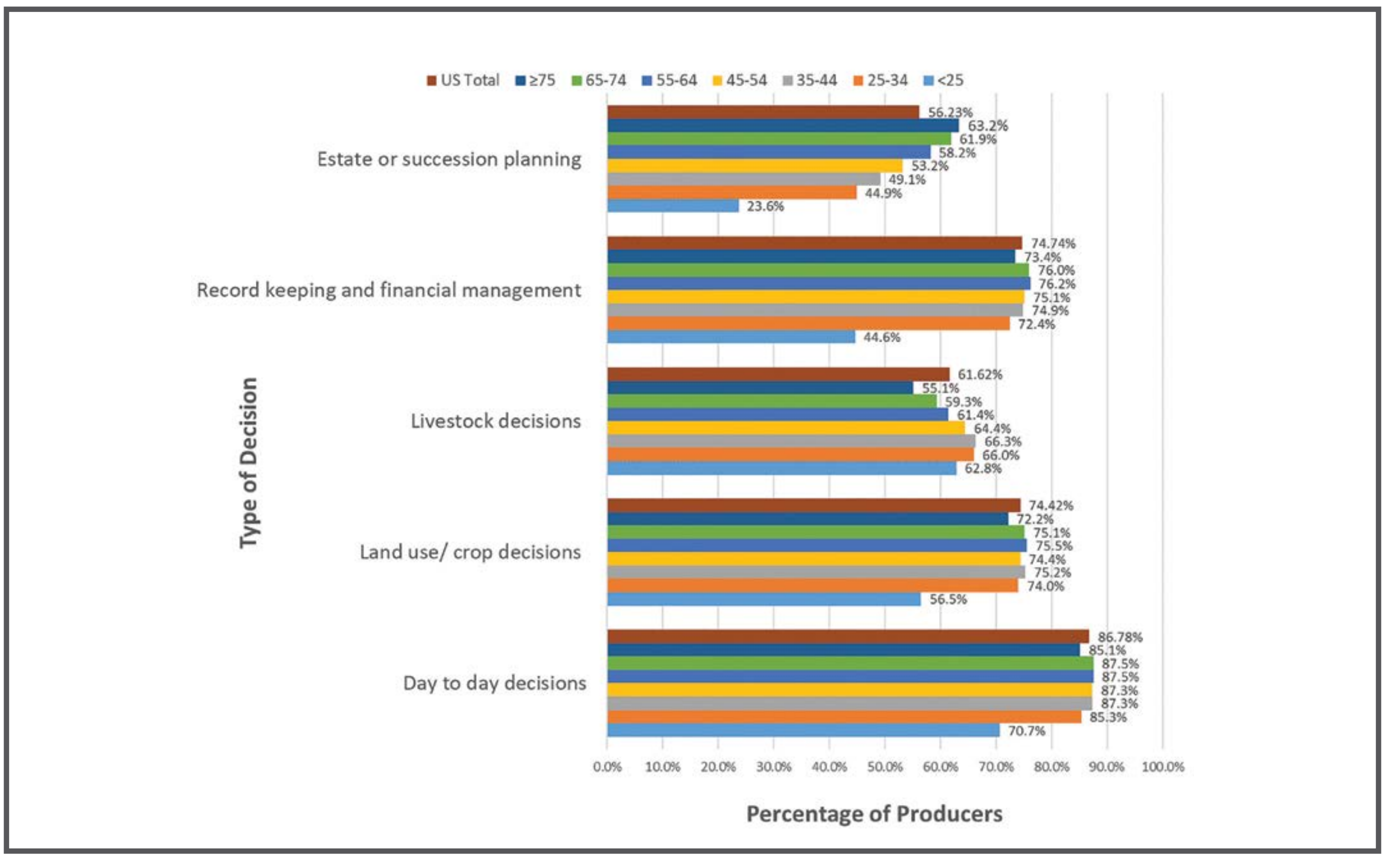

Figure 1. Involvement in Decision-Making for U.S. Producers and Based on Age Group (Source: Author calculations, USDA NASS 2017 Census of Agriculture). Note: With the exception of Land Use/Crop Decisions for 25–34 and 45–54, Record Keeping for 35–45 and 45–54, and Livestock for under 25 years old and 45–54, all other decision types by subgroups statistically differed from the U.S. population at the 5% level or the 1% level. The very large numbers to the subgroups makes the proportions test very sensitive.

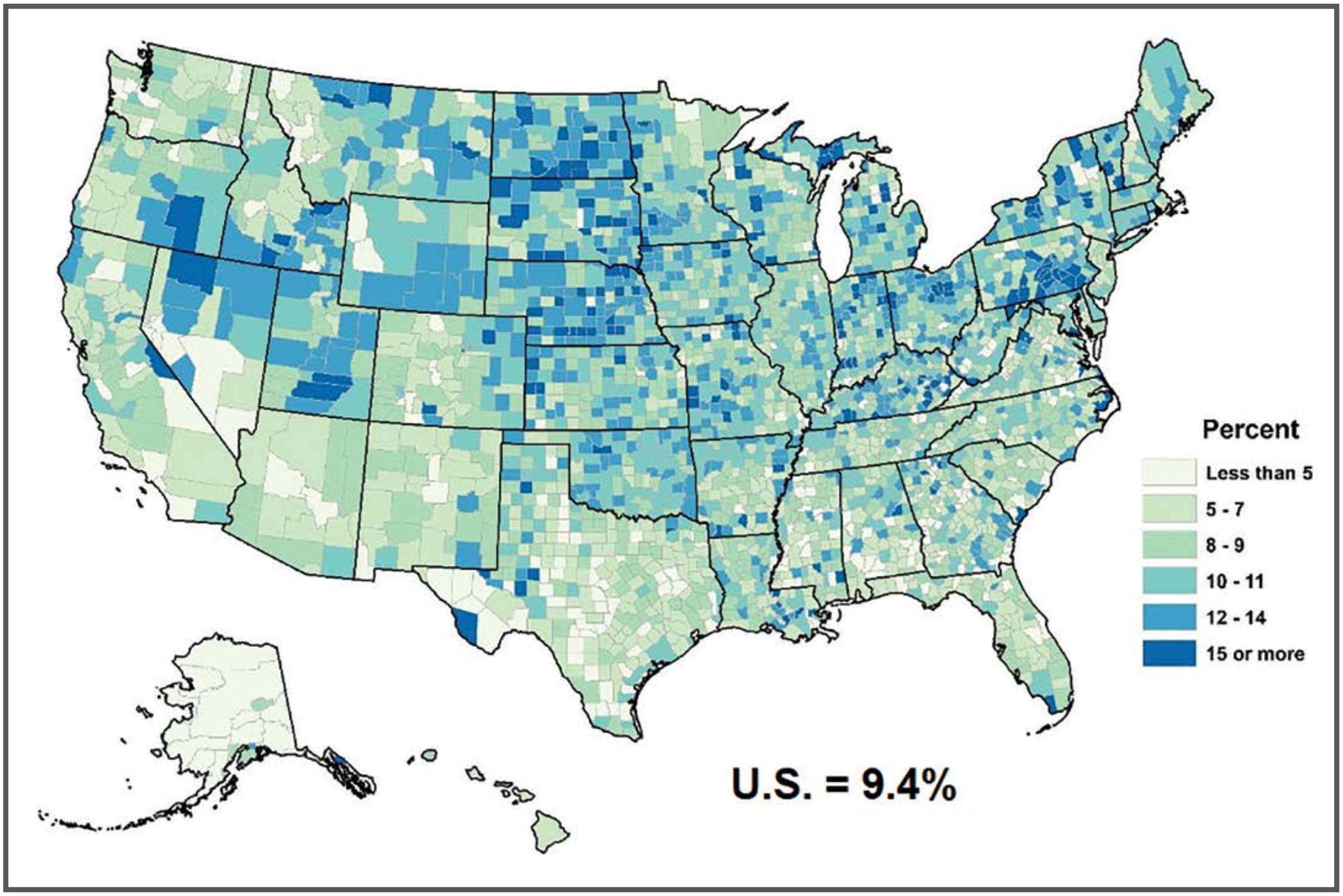

Figure 2. Young Producers, as a Percent of All Producers by County (Source: USDA NASS 2017 Census of Agriculture)

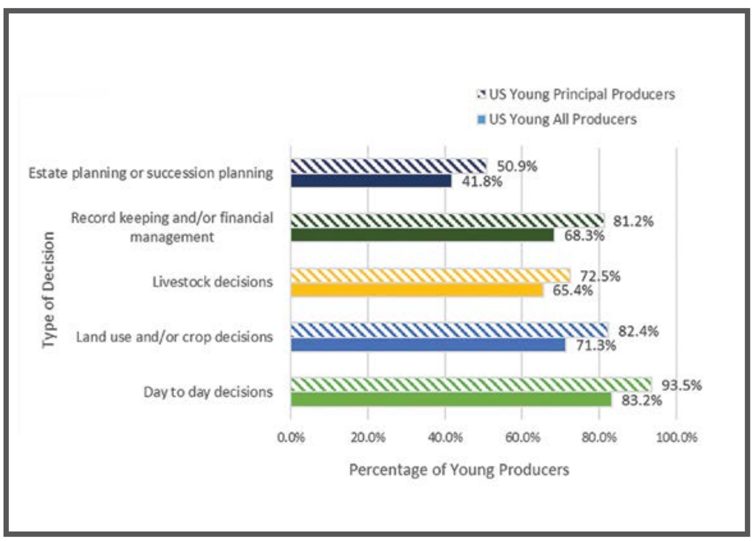

Figure 3. Involvement in Decision-Making by Young Producers (Source: USDA NASS 2017 Census of Agriculture)

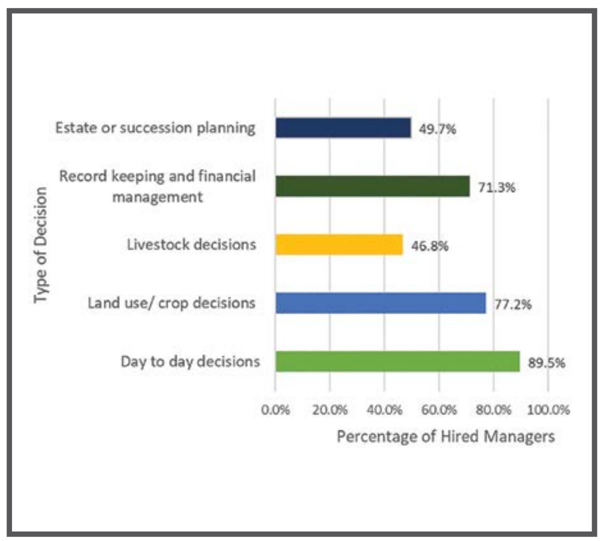

Figure 4. Involvement of Hired Managers in Decision-Making (Source: USDA NASS 2017 Census of Agriculture)

Table 1. Proportions Test on Decision-Making by Subgroups

Item	Day-to-Day	Land Use/Crop	Livestock	Financial	Estate/ Succession
Number of producers <35	236,138	202,285	186,729	192,586	117,251
Number of producers ≥35	2,950,329	2,530,154	2,095,061	2,541,028	1,911,680
Percentage of producers <35	0.827	0.708	0.654	0.675	0.411
Percentage of producers ≥35	0.947	0.812	0.673	0.816	0.614
Standard error	0.000788681	0.001039633	0.001147442	0.00109488	0.001479283
Z-score	152.2035	99.7717	16.1407	128.9611	137.2600
P-value	0	0	0	0	0

Source: Author calculations, USDA NASS 2017 Census of Agriculture

Table 2. Decision-Making of Young Producers Based on Production Regions

	Day-to-Day	Land Use/ Crop	Livestock	Financial	Estate/ Succession
Pacific	6.27%	6.46%	5.01%	5.87%	5.70%
Mountain	7.97%	8.10%	8.63%	7.85%	7.95%
Northern Plains	9.35%	9.72%	8.92%	10.24%	9.82%
Southern Plains	12.69%	12.25%	15.11%	12.63%	13.43%
Lake States	9.95%	10.00%	9.18%	9.87%	9.77%
Corn Belt	21.61%	21.87%	19.91%	22.51%	21.96%
Delta States	4.62%	4.53%	4.92%	4.72%	4.89%
Southeast	6.10%	5.89%	6.31%	5.87%	6.13%
Appalachian	12.23%	12.13%	13.16%	11.94%	12.15%
Northeast	9.22%	9.05%	8.86%	8.51%	8.19%

Source: Author calculations, USDA NASS 2017 Census of Agriculture

Potential for Genomics to Improve Feed Efficiency and Ranch Profitability





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Abstract

Feed inputs comprise one of the largest operational cost categories for cattle production. Thus, the economic sustainability of the beef industry can be positively affected by improving feed efficiency. Genomic testing could be used to select beef animals with superior feed efficiency. As such, this management tool offers the potential for economic improvement. We conduct firm-level budget analyses to estimate the potential profitability associated with increasing feed efficiency by 13% across two different cow-calf operation sizes, a base ranch of 200 cows versus 521 cows. We analyze two scenarios, cost savings from reduced feed keeping herd sizes the same, and using the reduced feed consumption per cow to grow the herd. Our results indicate that the smaller ranch does not see positive benefits during the first seven years for either scenario or discount rate (4% or 6%) analyzed. Our analysis indicates that smaller operations see positive benefits only in a 10-year planning horizon, and they are better off to keep herd size the same and improve profits through feed cost savings. Our analysis also indicates that increasing herd size through increased feed efficiency garners more benefits for the larger ranch after 10 years than reducing feed costs alone.

INTRODUCTION

The cow-calf sector is the foundational sector of the beef industry. The cow herd and related calf crop are the major determinants of beef supply in the United States. According to the last published census statistics in 2017, there were 31.72 million beef cows and heifers that had calved (USDA/NASS, 2019). Total value of cattle and calves residing on beef operations in 2017 equaled $31.43 billion.

Cow-calf operations are continuously searching for ways to improve profitability. Authorities and industry representatives promote new genetic technologies as being more efficient, capable of potentially increasing profits significantly (Garrick, 2011; Vestal et al., 2013; Thompson et al., 2014). One of the major advantages to genomic testing (as opposed to traditional growth and productivity measurements) is the decreased generation interval, as well as quicker recognition of superior traits. Calves can be genetically tested at birth and selection decisions can be made immediately, rather than waiting multiple years for production-driven decisions. However, many ranchers and cattlemen are hesitant to adopt new techniques such as genomic testing given potential risks, costs, and lack of knowledge regarding profitability. Little research has documented the potential economic advantages of technologies such as genomic testing to the U.S. beef industry, particularly cow-calf producers.

Feed costs remain one of the largest operational expense categories in the cow-calf sector. On average, feed accounts for 60% of the total cost of calf and yearling finishing systems; the cow-calf segment consumes about 70% of the total feed calories, whereas 30% is used by growing and finishing systems (Taylor, Kerley, and Schnabel, 2013). Berger (2017) indicates that feed costs can account for 40% to 70% of total annual cow costs for cow-calf producers. Given the importance of feed costs in determining profitability, it is expected that feed efficiency improvements could have a major impact on the economic sustainability of the cow-calf sector in addition to the feeding sector (Cassady, 2016).

Despite improvements made in genomic testing and the potential impact of feed efficiency on ranch profitability, cow-calf producers generally lack knowledge about these concepts. A survey conducted in 2013 found that only 36.2% of commercial cow-calf producers correctly defined feed efficiency (Weaber et al., 2016). Additionally, only 8.5% of producers responded to the survey that they were "very knowledgeable" or "extremely knowledgeable" about methods to select for improved feed efficiency, and 41.2% indicated they were not at all knowledgeable of such methods (Weaber et al., 2016). Spangler (2018, 107) concludes that "the early, and in many cases premature, commercialization of genomic tests" has led to "confusion and angst among beef cattle producers" as these genetic evaluation tools have evolved. Weaber et al. (2016, 93) indicate that while "no direct price signal exists in the beef value chain for feeder cattle with different potentials for feed efficiency, cow-calf and feedlot producers may obtain increased profits through reduced feed cost per unit of output through selection for efficiency." They further conclude that more educational work must be done to aid producers in understanding methods for selection to improve feed efficiency.

Coupled with the lack of knowledge regarding genetic evaluation methods and feed efficiency, there is a lack of research indicating an economic benefit for commercial cow-calf producers to use genomics as a selection tool. Our objective is to evaluate the potential impact of using genomic testing to select for animals with increased feed efficiency on cow-calf operations. We achieve our objective by conducting enterprise budget analyses of cow-calf operations adopting genomic testing, recruiting more feed efficient animals into the cow herd, and thereby improving overall feed efficiency of the total herd. As part of our analysis we assess two separate scenarios. We analyze potential improvement in profitability emanating from (1) feed cost savings alone and (2) increasing herd size given improved carrying capacity coming from more feed efficient cows. Additionally, to understand potential differences across operation size, we analyze an enterprise with an original beef cow herd size of 200 head and compare that to an operation with 500 beef cows. We chose these two operation sizes because they represent operation sizes containing the largest portion of the beef cow herd nationally according to 2017 census statistics (USDA/NASS, 2019).

ANALYSIS ASSUMPTIONS

We assume the cow herd, once improved through genetic selection of feed efficient females, will consume 87% of the amount of feed compared to the original or base enterprise budget data. This assumption is based on an estimated potential feed efficiency improvement of 13% reported by Ibragimov (2018) for steers involved in feed experiments conducted at the University of Wyoming Sustainable Agriculture Research and Extension Center (SAREC). It is important to note that at the time of this writing, data was not available on potential differences in feed efficiency for cows. Thus, we are using this percentage based on steer data, and we are assuming that this level of improvement in beef cows is feasible. We use this only as a benchmark for our analysis.

Given our assumed benchmark of 13%, the percentage change in feed intake to achieve the same level of produced output was assumed to be a reduction of 1.85% per year for year one through seven of our cow-calf budget analyses (i.e., adding 15% of the herd that consumes 13% less feed reduces the average consumption for the herd by 1.85%). We further assume that these animals can be recruited into the herd via replacements from the calf crop rather than purchasing replacement heifers from seedstock producers.

It is important to note that during the transition period years one through seven, heifer animals are being selected and retained in the herd in the fall rather than being sold as calves. Change in feed consumption is assumed to only happen for the feed efficient animals retained. By the end of the fall of year seven, all of the cow herd is assumed to be replaced with feed efficient animals (7 years × 15% per year = 105% of herd; i.e., we are assuming that the whole herd is replaced by the end of year 7, which allows a fudge factor of 5% for reduced pregnancy rates among heifers, etc.). Thus, full benefits of a feed efficient herd are not realized until after year seven.

Given that in the budget analyses conducted, we assume that the improvement in feed efficiency happens over time, we used net present value (NPV) analysis. One important aspect of conducting an NPV analysis is the discount rate choice. While there are a number of potential discount rates, we utilize the same discount rate as reported by Ruff et al. (2016), who analyzed switching from a cow-calf-yearling operation to a stocker operation over time in northwestern Wyoming. They utilized a long-term real discount rate of 2% plus a 2% risk adjustment. Similarly, we use a 4% discount rate for our NPV analysis. We also use a 6% discount rate to understand sensitivity of results to a risk premium of 4% rather than 2%. We analyze two time horizons in our analysis. The first time horizon is NPV for the first seven years (i.e., the transition period), and then we analyze NPV for a 10-year horizon (i.e., the producer has the benefit of the whole herd being feed efficient for several years after the transition).

COW-CALF BUDGETS

As mentioned previously, we are interested in the economic impact of improved feed efficiency on operations with different herd sizes. Therefore, we used two base cow-calf budgets from which to conduct our analyses. The 200-head operation budget, based on production practices typical in southeastern Wyoming, was published by Eisele et al. (2011) (Table 1). The 500-head operation is based on Mountain Valley Ranches in Wyoming, appearing in Strauch (2008) (Table 2). Both budgets were completed after interviews with area producers to obtain and verify operational assumptions.

Our analysis assumed the weight of calves sold as 550 pounds for steers and 500 pounds for heifers. We assumed all calves were sold in October. We recognize that cow-calf operations vary in terms of their marketing times and weaning weights. However, these assumptions are consistent with modeling peak marketing of calves weaned in the fall as is commonly done.

Prices for steers and heifers were taken from Wyoming auction data reported by the Livestock Marketing Information Center for the years 2007–2015 (LMIC, 2018). Each year prices were deflated to 2015 and averaged for the analysis. Average prices for 550-pound steers and 500-pound heifers used in the analysis were $165.46/cwt and $156.53/cwt, respectively (Table 3).

Our analysis assumed sold cull cows and cull bulls were 1,200 pounds and 1,800 pounds, respectively. Given the availability of data on cull cows and cull bulls, these prices were taken from Colorado auction and Sioux Falls, South Dakota, auction data reported by the Livestock Marketing Information Center for the years 2007–2015; prices were averaged from both auctions. Each year, prices were deflated to 2015 and averaged across all years for the analysis. Average prices for 1,200-pound cull cows and 1,800-pound cull bulls used in the analysis were $69.81/cwt and $74.65/cwt, respectively (Table 4).

All prices received and costs paid are deflated to 2015, utilizing producer price index data reported by the USDA National Agricultural Statistics Service (NASS) (see Tables 3 and 4 for more detail on output prices used in the analysis). We deflate all final NPV results to 2019 dollars using the prices received index for livestock production (USDA/NASS, 2020) (i.e., in today's dollars, from the 2015 values used in the analysis).

EXPENSES ON GENOMIC TESTS

Genomic tests can be performed by various companies in the United States. We contacted the Zoetis and Igenity companies and received pricing lists for various genomic tests. The beef cattle genomic tests reporting information related to feed efficiency by Zoetis and Igenity cost $28/head and $25/head, respectively. Assuming no difference in accuracy of the tests across the two companies, and given the cost difference of the tests, we used the Igenity genomic test cost for our analyses. Genomic tests provide maternal traits, performance traits, and carcass traits (Table 5). We are mainly interested in tests related to performance traits regarding residual feed intake and average daily gain information of cattle. Cattle containing markers for these traits are used to select for cattle that are more feed efficient when determining which animals to use as replacement heifers. While genomic tests are available regarding carcass traits such as tenderness and marbling in this panel test, we could not find published research clearly linking carcass traits and feed efficiency or related price impacts. Moreover, Weaber et al. (2016) indicate that no price differentials exist for feed efficient feeder animals. So, we assume that there is no change in prices received for calves coming from feed efficient cows or with the markers for feed efficiency in our analysis.

We assume that genomic testing is conducted on all cows, bulls, and heifers in the first year (t=0 in the NPV analysis; i.e., the initial cost of testing is an investment cost) to provide a baseline regarding which animals are a priority for replacement. After the initial testing we assume the producers will conduct genomic testing only for heifers to inform replacement selection. Moreover, we assume that producers purchase bulls with traits for feed efficiency.

SCENARIOS ANALYZED

For the first scenario, feed cost savings alone, we assume that during the transition in years one through seven, feed consumption per female breeding animal per day was reduced by 1.85% annually. The cow herd size was assumed to remain the same for each operation size. We calculate the change in feed consumption, and from that we calculate the change in feed costs. Savings on operating interest is also calculated and assumed to occur as less operating money is borrowed to purchase feed.

Our second scenario assumed that feed savings per animal allowed the cow-calf enterprise to increase the size of the cow herd (i.e., we assume the carrying capacity of the ranch remains the same in terms of feed produced but additional cows can be added as herd feed efficiency improves). The increased cow herd was based on adjusted animal feed per head divided into total feed available (assumed to be constant for the operation). In the second scenario, the costs that varied on a per head basis were multiplied by the adjusted number of head for each year of the analysis, so total variable costs increased with the herd size in our analysis. Costs related to genomic testing, feed, heifer retention, interest on operating funds, and other operational costs on a per head basis were included in the change in total costs for this scenario. Revenues were also changed based on the number of calves sold (during the transition as the herd grows, heifer calf sales reflect the increased number retained and sales forgone, as well as increased number of calves sold) and cull animals sold given the increased herd size. All assumptions related to death loss, weaning percentages, and conception rates were held at the same rates on a per animal basis. It is important to note that this scenario assumes no change in fixed costs (i.e., we are assuming that the existing cow-calf facilities and machinery for the operation could accommodate the increased cow herd size without further capital investment). It also should be noted that in the second scenario we assume that the modest increase in number of animals stocked does not degrade ranch resources such as rangelands given reduced consumption per animal.

RESULTS

According to the first scenario, NPV for feed cost savings alone, the operation with 200 cows has an NPV of \$(406.62) or \$(920.83) given discount rates of 4% or 6%, respectively. This indicates that during the transition years accumulated cost savings would not be enough to overcome the investment in genomic testing (Table 6). As time passes, the benefits increase; after 10 years, NPV would range between \$4,605 and \$6,025—equaling \$23 to \$30 per head, depending on the discount rate used. Once the transition is complete and all savings are realized, the average nominal cost savings per year is \$3,202, or nearly \$246 per 1% improvement in feed efficiency for the herd.

Feed cost savings alone for the 521-cow herd size operation indicates that producers would receive benefits ranging from nearly \$2,206 or \$3,924, or \$4.23 to \$7.53 per head, by the end of year 7, depending on the discount rate (Table 6). Again, we see improvement in net benefits as time passes, and the NPV after 10 years would total between \$18,982 and \$23,450 (\$36.43 or \$45.01 on a per head basis). Once the transition is complete, the average nominal cost savings per year for this larger operation is \$9,719.56, or nearly \$748 per 1% improvement in feed efficiency for the herd. These results indicate that given operational practices and costs assumed in the budgets, larger operations may very well benefit more from improved feed efficiency than smaller operations.

Results for the second scenario, increased herd size from improved feed efficiency, indicate that NPV is reduced in both the seven-year and 10-year time horizons for the smaller ranch operation. The NPV for the seven-year horizon varies between \$(8,575.69) and \$(9,068.62), nearly double the negative NPV estimates for the feed savings alone scenario (Table 6). The increased net revenues after the transition is complete are \$6,389, or \$491.50 per 1% increase in feed efficiency. The moderate increase in calf sales is not enough to improve profitability given the added variable costs and investment in genomic testing for the time horizons analyzed in this scenario for the smaller ranch.

Consistent with our previous scenario, our results suggest that larger operations see more benefits from improved feed efficiency that allows them to increase herd size. Results for operations with a beginning herd size of 521 head would see a positive total NPV ranging from $885.38 to $3795.96, or $1.51 to $6.47 per head, by the end of year seven, depending on the discount rate used (Table 6). Unlike the smaller operation, our projections indicate that the larger ranch operation sees more benefits from the increased cow herd scenario by year 10 than from reduced feed costs alone. The NPV in year 10 ranges from $43,640.22 to $53,557.85, or $74.34 to $91.24 on a per head basis. The increased net revenues after the transition is complete for this larger operation are $24,770, or $1,905 per 1% increase in feed efficiency. Given the cost structure and operational assumptions for the larger ranch, the added calf sales are able to improve profitability enough to overcome added genomics and operational costs beyond the feed cost savings scenario. Our results suggest that even with the shorter time horizon, larger operations could see positive benefits from increasing herd size by improving feed efficiency of the herd.

CONCLUSIONS

Overall, our results indicate that if cow-calf producers are able to improve feed efficiency by at least 13%, the cost of genomic testing could pay for itself over a period of 10 years. However, this investment does not break even by year seven of our analysis for the smaller cow-calf operation assuming they just bank feed cost savings and don't use the added feed efficiency to grow herd numbers. Our analysis shows that smaller operations would not realize positive NPV benefits if they were increasing herd sizes until well after year seven. Given a longer time horizon of 10 years, increasing herd size would result in higher benefits than feed efficiency alone for the larger cow-calf operation assumed in our analysis. However, it is important to remember that we assume the forage resources of the ranch are not degraded by the added number of animals. Overall, our estimates do point to some interesting differences in results when comparing benefits of improved feed efficiency across operation sizes and scenarios.

Another implication is that of time horizon for cow-calf producers. Our results suggest that even with the shorter time horizon, larger operations could see positive benefits from either scenario, reducing feed or increasing cow herd. This is not true for the smaller ranch operation in our analysis. The smaller ranch sees negative NPVs for all assumed scenarios at the end of the seven-year period. It is not until the 10-year horizon that the smaller operations see positive NPVs.

It is important to understand the limitations of the budget analyses reported here. While they are informative and provide important baseline estimates, it is important to understand that ranches with less efficient production, lower conception rates, and lower weaning rates would receive lower benefits than estimated here. Additionally, our budget analyses assume no price variability. Price variability would likely reduce the potential benefits estimated here. Moreover, we assume a perfectly competitive market condition and that prices are unaffected by adoption of this technology. Obviously, if there is widespread adoption of genomic testing and selection for feed efficient animals occurs, our results point to incentives for individual producers to increase herd sizes—which in turn could result in larger supplies of feeder cattle and animals being slaughtered.

It is important to recognize that feed efficiency improvement might vary in different climatic conditions and across different herd sizes. Moreover, feed efficiency improvement might also vary across cow-calf operations compared to the assumptions we used in this analysis. While we use actual data from experiments conducted at SAREC to motivate our analyses, it should be noted that the data did not actually link genomic tests to cow performance. Moreover, the potential tradeoffs in cattle characteristics on selecting for feed efficiency are not known. Improving feed efficiency may impact other traits such as quality, docility, calving ease, etc. Future research on cattle characteristics and documenting genetic traits related to feed efficiency for both the cow-calf and feedlot segments is needed to inform future economic analyses. Without such data, the accuracy of economic analyses is driven by assumptions rather than observation. Regardless of these shortcomings, this analysis points to the potential to use genomic testing to improve ranch profitability as long as feed efficiency improvement realized is of the magnitude assumed here.

FOOTNOTE

[1] Dr. Matt Spangler, Professor and Beef Genetics Specialist at the University of Nebraska, indicated in a phone interview on December 19, 2019, that no outside testing or validation by a third party has been conducted regarding accuracy of these tests.

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Table 1. Cow-Calf Budget, 200 Head, 2015 (Base Year)						
Receipts	**Number of Head**	**Average Weight**	**Units**	**Adjusted Sale Price/ Unit 2015**	**Value/Cow**	**Total Value**
Steers	90	550	lbs	$1.65	$409.52	$81,904.59
Heifers	60	500	lbs	$1.57	$234.79	$46,958.67
Cull cows	30	1200	lbs	$0.70	$125.66	$25,132.49
Cull bulls	2	1800	lbs	$0.75	$13.44	$2,687.54
Total Receipts					**$783.42**	**$156,683.29**
Expenses	**Units/Cow**	**Total Units**	**Units**	**Cost/Unit**	**Cost/Cow**	**Total Costs**
Feed Expenses						
Grass hay	0.75	150.00	tons	$129.44	$97.08	$19,415.67
Alfalfa hay	0.50	100.00	tons	$141.65	$70.82	$14,164.89
Salt/mineral (50/50 mix)	0.25	7500.00	lbs	$0.74	$27.93	$5,586.58
Protein supplement tubs	1.00	200.00	lbs	$0.50	$45.06	$9,011.80
Federal grazing	1.15	3.45	AUMs	$21.97	$75.79	$15,157.77
State land grazing	1.15	1.38	AUMs	$21.97	$30.32	$6,063.11
Private pasture lease grazing	1.15	2.875	AUMs	$20.59	$56.17	$11,234.22
Total Feed Expenses					**$403.17**	**$80,634.04**
Reproduction Costs						
Breeding bulls	0.01	2	bull	$6,020.08	$60.20	$12,040.16
Replacement heifers/cows	0.17	34	heifer	$1,209.35	$205.63	$41,126.11
Total Reproduction Costs					**$265.83**	**$53,166.26**
Animal Health						
Veneration service	1.00	200	cow	$3.66	$3.66	$732.67
Medication & supplies	1.00	200	cow	$2.44	$2.44	$488.44
Vaccinations cow/calf pair	1.00	200	cow	$18.32	$18.32	$3,663.33
Bull testing & vaccine	0.035	7	bull	$36.63	$1.28	$256.43
Total Animal Health					**$25.70**	**$5,140.88**
Miscellaneous Labor						
Custom labor	1	total cost		$1,831.67	$9.16	$1,831.67
Total Labor					**$9.16**	**$1,831.67**
Marketing & Transportation						
Transportation (liability, fuel included)		1	yr.	$2,442.22	$12.21	$2,442.22
Marketing commission	1.06	212	head	$24.42	$25.89	$5,177.51
Total Marketing & Transportation					**$38.10**	**$7,619.73**
Total Variable Costs					***$741.96***	***$148,392.58***
General Overhead Costs						
Facility maintenance		1	yr.	$1,221.11	$6.11	$1,221.11
Machinery repairs & maintenance		1	yr.	$9,101.92	$45.51	$9,101.92
Interest		1	yr.	$10,817.82	$54.09	$10,817.82
Depreciation: machinery & vehicles		1	yr.	$17,692.58	$88.46	$17,692.58
Property taxes		1	yr.	$253.25	$1.27	$253.25
Miscellaneous		1	yr.	$4,273.89	$21.37	$4,273.89
Total General Overhead Costs					**$216.80**	**$43,360.56**
Total Costs					**$958.77**	**$191,753.15**
Return Over Variable Costs					*$41.45*	*$8,290.71*
Net Income					***($175.35)***	***($35,069.86)***

Table 2. Cow-Calf Budget, 521 Head, 2015 (Base Year)						
Item	**Quantity**	**Average Weight/ Unit**	**Units**	**Adjusted Sale Price/ Unit 2015**	**Value/Cow**	**Total Value**
Livestock Revenue						
Steers	234	550	lbs	$1.65	$408.74	$212,951.94
Heifers	182	500	lbs	$1.57	$273.40	$142,441.30
Cull cows	52	1200	lbs	$0.70	$83.61	$43,562.98
Other Revenue						
Excess Hay	434.50		ton	$28.97	$24.16	$12,587.15
Total Revenue					**$789.91**	**$789.91**
Variable Costs						
Hay	1,026.50		ton	$93.79	$184.79	$96,276.06
Feed purchased	47.80		ton	$729.90	$66.97	$34,889.27
Federal lease	2,911.00		AUM	$5.40	$30.16	$15,712.47
Deeded range	1,459.00		AUM	$2.68	$7.52	$3,917.27
Deeded meadow	1,058.00		AUM	$2.68	$5.45	$2,840.62
Bull charge	1.00		head	$27.43	$27.43	$14,292.73
Veterinary expense			$		$13.65	$7,110.11
Fuel, lube, etc.			$		$30.95	$16,126.09
Supplies			$		$17.96	$9,356.80
Repairs			$		$30.91	$16,105.22
Utilities			$		$22.28	$11,610.45
Freight/yardage			$		$0.57	$297.70
Miscellaneous			$		$5.48	$2,856.01
Interest on operating expenses			$		$11.90	$6,201.70
Total Variable Costs					**$456.03**	**$237,592.50**
Return Over Variable Costs					*$333.88*	*$173,950.86*
Fixed Costs						
Taxes			$		$40.30	$20,995.07
Insurance			$		$16.84	$8,773.92
Interest on breeding stock (4%)			$		$36.23	$18,873.59
Interest on machinery/equipment			$		$105.18	$54,796.97
Interest in vehicles (4%)			$		$2.18	$1,133.78
Depreciation			$		**$108.84**	**$56,705.62**
Total Fixed Costs					**$309.56**	**$161,278.95**
Total Costs					**$765.59**	**$398,871.45**
Net Income					***$24.32***	***$12,671.92***

Table 3. 550-Pound Steer and 500-Pound Heifer Prices in October, Wyoming Auction						
Steer	500-550 lb	550-600 lb	550 lb	Price Paid	Price Received	Deflating Price Received to 2015
Year	**Price in $ for 100 lb**			**Price Indexes**		
2007	121.65	116.39	119.02	71.9	84.8	$140.3
2008	107.60	100.50	104.05	81.9	92.9	$112.0
2009	106.76	99.60	103.18	79.4	81.8	$126.1
2010	127.10	119.15	123.13	81.9	82.8	$148.7
2011	157.89	148.89	153.39	91.0	101.0	$151.9
2012	161.78	154.88	158.33	95.0	106.1	$149.3
2013	189.79	179.29	184.54	96.7	108.1	$170.7
2014	301.88	285.56	293.72	101.9	109.0	$269.5
2015	228.25	213.35	220.80	100.0	100.0	$220.8
Average						**$165.46**
Heifer	450-500 lb	500-550 lb	500 lb	Price Paid	Price Received	Deflating Price Received to 2015
Year	**Price in $ for 100 lb**			**Price Indexes**		
2007	114.12	110.14	112.13	71.9	84.8	$132.2
2008	95.59	91.88	93.74	81.9	92.9	$100.9
2009	97.71	93.94	95.83	79.4	81.8	$117.1
2010	119.95	114.21	117.08	81.9	82.8	$141.4
2011	147.54	141.03	144.29	91.0	101.0	$142.8
2012	152.40	145.11	148.76	95.0	106.1	$140.3
2013	176.27	172.20	174.24	96.7	108.1	$161.2
2014	300.64	280.74	290.69	101.9	109.0	$266.7
2015	212.01	200.49	206.25	100.0	100.0	$206.3
Average						**$156.53**

Table 4. Prices for Cull Cows, 1200 Pounds, and Cull Bulls, 1800 Pounds						
Cull Cows	**Colorado Auction**	**Sioux Falls, SD, Auction**	**Average Price**	**Paid**	**Received**	**Deflating Price Received to 2015**
Year	**Price in $ for 100 lb**			**Price Indexes**		
2007	47.13	48.73	47.93	71.9	84.8	56.49
2008	48.61	51.99	50.30	81.9	92.9	54.13
2009	44.05	45.75	44.90	79.4	81.8	54.87
2010	52.12	55.57	53.84	81.9	82.8	65.01
2011	64.68	68.54	66.61	91.0	101.0	65.94
2012	75.65	73.33	74.49	95.0	106.1	70.23
2013	76.26	74.92	75.59	96.7	108.1	69.94
2014	101.34	104.53	102.94	101.9	109.0	94.45
2015	94.46	100.04	97.25	100.0	100.0	97.25
Average						**$69.81**
Cull Bulls	**Colorado Auction**	**Sioux Falls, SD, Auction**	**Average Price**	**Paid**	**Received**	**Deflating Price Received to 2015**
Year	**Price in $ for 100 lb**			**Price Indexes**		
2007	47.22	60.10	53.66	71.9	84.8	63.25
2008	48.67	60.04	54.36	81.9	92.9	58.49
2009	44.01	54.47	49.24	79.4	81.8	60.18
2010	52.21	63.11	57.66	81.9	82.8	69.61
2011	64.11	74.67	69.39	91.0	101.0	68.70
2012	75.36	84.47	79.91	95.0	106.1	75.35
2013	76.22	83.14	79.68	96.7	108.1	73.72
2014	101.45	110.95	106.20	101.9	109.0	97.44
2015	94.30	116.01	105.15	100.0	100.0	105.15
Average						**$74.65**

Table 5. Genomic Test Information Provided by Igenity Company		
Maternal Traits	**Performance Traits**	**Carcass Traits**
Calving ease maternal	Residual feed intake	Tenderness
Stayability	Average daily gain	Marbling

Table 6. Net Present Value (NPV) Estimates Across Ranch Sizes, Scenarios, and Discount Rates				
Scenario 1: Reducing Feed, Base Operation Size 200 Cows				
	Discount Rate 4%		**Discount Rate 6%**	
Time Horizon	**Total NPV**	**Per Cow**	**Total NPV**	**Per Cow**
7 years	$(406.62)	$(2.03)	$(920.83)	$(4.60)
10 years	$6,025.70	$30.13	$4,605.75	$23.03
Scenario 2: Increasing Cow Herd to 225 Head, Base Operation Size 200 Cows				
7 years	$(8,575.69)	$(38.11)	$(9,068.62)	$(40.30)
10 years	$4,260.54	$18.94	$1,960.11	$8.71
Scenario 1: Reducing Feed, Base Operation Size 521 Cows				
7 years	$3,923.80	$7.53	$2,205.64	$4.23
10 years	$23,450.06	$45.01	$18,982.39	$36.43
Scenario 2: Increasing Cow Herd to 587 Head, Base Operation Size 521 Cows				
7 years	$3,795.96	$6.47	$885.38	$1.51
10 years	$53,557.85	$91.24	$43,640.22	$74.34

Farmland Investment: A Portfolio Perspective


By Ashraf Noumir and Michael Langemeier

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Abstract

The purpose of this study is to examine the return and risk of farmland investment from a portfolio perspective. Our goals are to answer two questions. First, from a portfolio perspective, how does farmland investment fit into a portfolio of other traditional asset classes? Second, what are the optimal weights of farmland investments relative to other assets in the portfolio and how do these weights change with different portfolio selection strategies? Results indicate that farmland is a good risk diversifier and the portfolio has a higher reward-to-risk ratio with farmland investment.

INTRODUCTION

One of the most pioneering breakthroughs in the field of modern finance was the mean-variance (MV) model. In his paper titled "Portfolio Selection," published in the *Journal of Finance* in 1952, Harry Markowitz introduced the first mathematical model examining the relationship between return and risk within the context of risk diversification. The MV model introduced an answer to an instrumental question: How should a rational investor allocate their wealth among a set of assets with risky payoffs? Although Markowitz used one class of assets in his paper,[1] namely securities, the MV model can be applied to a wide range of asset classes. The MV model and subsequent models such as Sharpe's Single-Index Model (SIM) (1963) and Sharpe (1964) and Lintner's (1965) Capital Asset Pricing Model (CAPM) included financial assets in applications. For instance, assumptions such as no transaction costs, asset divisibility, and asset marketability—though not perfectly held in capital markets—are harder to hold than other classes of assets. Of course, the main goal of studies that examined portfolios of different asset classes was the same as Markowitz's: finding an asset allocation that minimized risk for a given level of return or maximized return for a given level of risk.

The MV model and other subsequent asset pricing models have proven to be theoretically very useful and of great importance to academics and practitioners alike. However, a large body of literature about real world applications has emerged. These studies often refer to the gap between theory and practice. Various attempts have been made to try to narrow this gap, either by adopting different techniques for parameter estimation or relaxing the model assumptions to be more realistic. Others have questioned the core of the MV model or the core of modern finance theory. Jensen, Black, and Scholes (1972) tested the applicability of asset pricing models using monthly data for all the stocks listed in the New York Stock Exchange (NYSE) from January 1926 to March 1966. The authors found a weak positive relationship between risk and return. In asset pricing terminology, an asset's expected return is not directly proportional to its systematic risk—beta (β).

Baker (2016) went further along the same line by using time series data of security prices from 1963–2014. His overall conclusion was that "beta (β) has continued to fail as predictor of future returns." However, when more asset classes are considered, the positive relationship between risk and return across asset classes shows up. It is worth distinguishing between assets and asset classes. By asset class we mean a group of assets that share common characteristics and are subject to the same rules and regulations. The most common asset classes are equities, bonds, real estate, and commodities. Empirical evidence suggests that diversifying across asset classes has more diversification benefits than diversifying across assets. Motivated by that, in this paper, we form a portfolio comprised of financial and non-financial assets. One of the non-financial assets that has shown low correlation with traditional financial assets and has returns that, for the previous decade, surpassed the returns on financial assets is farmland. Indeed, many investors, mainly institutional investors,[2] are seriously considering adding farmland investments to their portfolio not only because of return and variance aspects of farmland but also as a hedge against inflation (e.g., Hancock Agricultural Investment Group). In addition, farmland assets are the dominant asset class in a typical agricultural portfolio. As reported by Moss and Katchova (2005), farmland constitutes the dominant portion in the U.S. farm sector's balance sheet.

In this study, we are examining farmland investment within a portfolio context. In particular, we are studying how farmland would fit into a portfolio comprised of traditional financial asset classes over the time period 1973–2017. Our main goal is to answer two questions. First, from a portfolio perspective, how does farmland investment fit into a portfolio consisting of traditional asset classes? Second, what are the optimal weights of farmland investments relative to other assets in the portfolio and how do these weights change with different portfolio selection strategies?

Our work contributes to the existing literature by providing additional robust evidence of the attractiveness of farmland investment from a portfolio perspective by looking at farmland performance and its relative portfolio weight over different portfolio selection methods, namely the mean-variance (MV), minimum-variance, equally weighted, and equal-risk contribution portfolios. The remainder of this paper is organized as follows: literature review, methodology and data, results, and conclusions.

LITERATURE REVIEW

Widening asset classes in a portfolio leads to better portfolio performance. This is what most of the multi-asset class portfolio literature shows (Madhogarhia and Lam, 2015; Bekkers, Doeswijk, and Lam, 2009; Bessler and Wolff, 2015). For instance, Madhogarhia and Lam (2015) used dynamic asset allocation (DAA) to compare the performance of asset classes and the performance of a portfolio comprised of different asset classes. Assets were categorized in six groups (large cap stocks, small cap stocks, long-term government bonds, long-term corporate bonds, intermediate-term government bonds, and U.S. Treasury bills). Data was divided into two periods: 1954–1983 was used to estimate the long-term return for each asset class and 1984–2013 was used as the investment horizon for each of the six asset classes. Returns were calculated as geometric means over an eight-year period. Results show that DAA generated a higher-risk adjusted return and a lower standard deviation than each of the six asset classes independently.

With regard to comparing the performance of portfolios, using 10 asset classes (stocks, private equity, real estate, hedge funds, commodities, high yields, credits, bonds, inflation linked bonds, and cash), Bekkers, Doeswijk, and Lam (2009) illustrated that incorporating non-traditional asset classes into the portfolio construction process leads to added diversification benefits between 0.40% and 0.93%. Moreover, the additional return was 0.56% for the same level of risk without non-traditional assets. Two approaches were followed to derive the optimal portfolios comprised of the different asset classes. The first approach was the traditional MV model. The outcome of this model showed that adding real estate, commodities, and high-yielding bonds to a traditional portfolio comprised of cash, stocks, and bonds led to more diversification benefits. The second approach was the market portfolio model (which implies assessing the weights of asset classes in the market portfolio). The results showed an improvement in portfolio performance and showed relatively small weights of non-traditional asset classes in the market portfolio compared to traditional asset classes.

Bessler and Wolff (2015) examined the improvement of the performance of a traditional portfolio (portfolios comprised of stocks and bonds) resulting from the inclusion of commodity investments in the portfolio. Commodity indices were obtained from the S&P Goldman Sachs commodity index family. The authors analyzed both in-sample and out-of-sample outcomes of this inclusion from the perspectives of different asset allocation strategies (i.e., MV, Black-Litterman, risk-parity, and equally and strategically weighted portfolio). Their results suggested that across different asset allocation strategies, industrial and precious metals and energy generally improved the performance of a traditional portfolio in both in-sample and out-of-sample results.

Agricultural assets are one of the asset classes that has grabbed the attention of both academics and practitioners alike. In fact, over previous decades, farmland earned returns that are substantially higher than other non-agricultural assets (Bjornson and Innes, 1992) while also providing a superior hedge against inflation due to the positive correlation between farmland returns and inflation (Feng and Hayes, 2016). Baker, Boehlje, and Langemeier (2014) found that current farmland price-to-rent ratios were higher than historical ones. Moreover, there was a low correlation between farmland and traditional assets.

Aiming at studying the potential value of adding farmland assets to the portfolio held by institutional investors, Lins, Sherrick, and Venigalla (1992) examined four asset classes: stocks, bonds, real estate, and farmland. They focused on portfolios held by institutional investors, mainly dominated by stocks and bonds. Annual data was used covering returns for the time period 1967–1988. Since returns of two of the asset classes (real estate and farmland) are based on appraisals and not actual sales, a test for appraisal bias was conducted following the procedure proposed by Firstenberg, Ross, and Zisler (1988). Interestingly, the findings showed that even when there was increased volatility for returns on farmland or lower farmland returns, farmland improved portfolio performance.

By incorporating farmland into an internationally diversified portfolio, Painter (2000) showed that even at an international level farmland is still a good risk diversifier. He incorporated Saskatchewan farmland into an internationally diversified portfolio consisting of equities in six developed countries in addition to equities in Canada and 90-day Treasury bills. His findings suggest that farmland has considerable diversification benefits for medium-risk portfolios and minimal diversification benefits for low-risk and/or high-risk portfolios.

Wan et al. (2015) assessed the role played by timberland assets in a portfolio of risky investments. Viewing both static and dynamic portfolio selection, the study showed that adding timberland investment to a portfolio of risky assets improves the performance of the portfolio. Two optimization methods were used, the mean-conditional value at risk (MCVaR) and the mean-variance (MV) models. The asset classes that were considered were large cap stocks, small cap stocks, Treasury bonds, Treasury bills, and timberland. Four scenarios, each with its own constraint, were considered. The first scenario used 20%, 15%, 10%, and 5% minimum asset allocation to large cap stocks, small cap stocks, Treasury bonds, and Treasury bills, respectively. The second scenario restricted the stock group and bond group by minimum and maximum weights of 30% to 70% and 20% to 50%, respectively. Scenarios three and four imposed 10% maximum weight to timberland assets in scenarios one and two, respectively. Quarterly data from 1987–2011 was used in the study. Results suggested that adding timberland to the portfolio improved the efficient frontier in both MCVaR and MV models, with a better improvement using the MCVaR model. The study also showed that the mixed portfolio was dominated by timberland and Treasury bonds.

Scholtens and Spierdijk (2010) used the MV framework to assess the potential diversification benefit of adding timberland to a well-diversified portfolio that consists of stocks, bonds, real estate, and a commodity index. Their findings show that adding publicly traded timberland investment to the portfolio does not significantly improve the portfolio performance. Adding the private equity timberland to the well-diversified portfolio shows mixed results depending on whether or not the return is unsmoothed. Results show that the smoothed return significantly improves the MV portfolio performance, but the unsmoothed return does not. Mei (2016) also found a similar result. He adopted the Heckman procedure to extract information from timberland trading prices, with the aim of constructing transaction-based indices of private equity timberland investment. The transaction-based index and unsmoothed index show very little diversification benefits to the overall portfolio.

METHODOLOGY AND DATA

Given a required mean return, $\boldsymbol{k}$, a typical MV model is

$$\min_{X} \boldsymbol{X}^{`}\,\Omega\,\boldsymbol{X} \tag{1}$$

$$S.T\ \boldsymbol{X} \geq 0 \tag{2}$$

$$\boldsymbol{C}^{`}\boldsymbol{X} = k \tag{3}$$

where $\boldsymbol{X}$ is a vector of asset weights, $\boldsymbol{\Omega}$ is the covariance matrix of the assets considered, and $\boldsymbol{C}^{`}$ is the transpose of the mean return of each asset. The first constraint implies that all asset weights should be greater than zero (no short selling is allowed). It is worth mentioning that in many portfolio selection applications, short selling is allowed; however, short selling is beyond the scope of this paper.

It is widely known that portfolio selection models are very sensitive to estimation errors. As reported by Chopra and Ziemba (1993), portfolios are sensitive to estimation errors related to the mean return and the covariance matrix. However, portfolios are 10 times more sensitive to errors in estimating the mean return than to errors in estimating the covariance matrix. In other words, errors in estimating the covariance matrix have less effect on the optimal portfolio than errors in mean estimation. With this in mind, a risk-based portfolio enables us to avoid errors in estimating the mean return simply by looking only at the covariance matrix.

Within the context of risk-based portfolios, there are many portfolio selection models. Among them are the minimum-variance portfolio, equal-risk portfolio, and equally weighted portfolio. With the minimum-variance portfolio, we typically minimize the portfolio variance without constraining expected return. One of the major limitations of the minimum-variance portfolio and even the MV portfolio is the concentration of risk in the portfolio (Clarke, De Silva, and Thorley, 2006). With an aim to solve the problem of risk concentration, the equal-risk contribution portfolio uses an equal risk contribution from each asset class. Following Chaves et al. (2012), the portfolio standard deviation σ_P can be depicted as

$$\sigma_P = \sqrt{\sum_{i=1}^{N}\sum_{j=1}^{N} X_i X_j \sigma_{ij}} \tag{4}$$

where σ_{ij} is the covariance matrix between X_i and X_j. We can calculate the marginal risk contribution (MRC) of X_i as

$$MRC_i = \frac{\partial \sigma_P}{\partial X_i} = \sum_{j=1}^{N} X_j \ .\sigma_{ij} = cov(r_i, r_P) \tag{5}$$

where r_i and r_P are the return on X_i and the portfolio, respectively. To break down the portfolio risk into its components, Chaves et al. (2012) proposed the measure of total risk contribution (TRC) for X_j as

$$TRC_i = X_i \cdot \frac{\partial \sigma_P}{\partial X_i} = \sum_{j=1}^{N} X_i \, . X_j \ \sigma_{ij} = X_i \, . cov\,(r_i, r_P) \tag{6}$$

The TRC for the portfolio is the summation of TRC_i for the portfolio components as

$$\sum_{i=1}^{N} TRC_i = \sum_{i=1}^{N} X_i \, . cov\,(r_i, r_P) \tag{7}$$

The objective of equal-risk contribution portfolio is to minimize the following:

$$\sum_{i=1}^{N}\sum_{j=1}^{N}(TRC_i - TRC_j)^2 \tag{8}$$

$$S.T. \sum_{i=1}^{N} X_i = 1 \tag{9}$$

With the equally weighted portfolio approach, each asset is attributed the same weight in the portfolio regardless of the metrics specific to that asset. This portfolio strategy is efficient when assets have similar covariance coefficients. However, as is almost always the case, it might lead to less risk diversification when there are significant differences in the covariance coefficients among assets (DeMiguel, Garlappi, and Uppal, 2007).

Our analysis is based on annual values of west central Indiana farmland, S&P 500, gold, Real Estate Investment Trust (REIT) Index, and three-month U.S. Treasury bill rates for 44 years (from 1973–2017). We relied on the Center for Research in Security Prices (CRSP)[3] database to obtain and compute the S&P 500 return. Data on historical gold prices was obtained from United Nations Conference on Trade and Development (UNCTADstat). The Purdue Agricultural Economics Report was used as the source for data on Indiana farmland values and cash rents; based on this data, return on farmland in west central Indiana was calculated as the sum of two components: return from cash rent and return from capital gains. It is worth noting that we avoided the differential tax treatment of the assets considered by narrowing our focus on pre-tax returns. Also, the farmland return data is the average of return data in west central Indiana. This might suggest potential measurement error. However, as reported by Cannella and Waterman (2014), the most common approach for determining the value or the rental rate of farmland is to check the regional data and adjust it conditional on other arrangements. In other words, landlords and tenants rely on regional data to get information about the market price or the rental rate of a certain parcel.

RESULTS AND DISCUSSION

Descriptive statistics indicate that over the sample period farmland had the highest mean return among the asset classes considered. As shown in Table 1, over the study period, the average farmland return is 12% followed by 10% for S&P 500, 8% for gold, and 5% for both three-month Treasury bills and REIT. Table 1 also shows another interesting feature of farmland. Its standard deviation is the lowest among risky assets (i.e., 0.13), whereas the highest standard deviation is 0.26 for gold. Treasury bills had the smallest standard deviation among the asset classes considered, at 0.04.

In Table 2, we can see the negative correlation and covariance between farmland returns and the other three risky asset classes. This indicates that farmland exhibits good diversification potential. In addition, the positive correlation between S&P 500 and REIT indicates that REIT would increase risk if REIT were added to a stock portfolio.

As a baseline scenario, we start by illustrating the MV efficient frontier. As illustrated in Figure 1, the MV frontier shows the highest expected return for every level of variance. For instance, a 12% return corresponds to a variance (risk) level of 0.019 and a 10% return is associated with a variance level of 0.007. Farmland was an important component of the MV frontier. For example, the asset allocation for the low-risk portfolio was 0.260, 0.138, 0.133, and 0.469 for the S&P 500, gold, REIT, and farmland, respectively. This portfolio had a return of 10% with a variance of 0.007. For the high-risk portfolio, 100% of the allocations were concentrated in farmland, indicating that farmland is an attractive investment for investors aiming to maximize the return on their investment. Given our sample period and sampling frequency, farmland assets outperformed the other asset classes (S&P 500, gold, REIT) in terms of both return and risk. The Sharpe ratio for the high-risk portfolio (which in this case is 100% farmland) was 0.53. For the minimum-variance portfolio, the Sharpe ratio was 0.59, which suggests that even though farmland by itself is a good investment, incorporating farmland in a portfolio leads to a higher-risk adjusted return.

When we look at the outcome of an equal-risk contribution portfolio (Table 3), farmland appears to still be dominating the portfolio—but with a weight of 33.6%, which is less than the 47% in the minimum-variance portfolio. According to Table 3, the amount of risk added to the portfolio by having 33.6% of it in farmland is the same amount of risk that results from having 24.3% of it in S&P 500. Compared to a Sharpe ratio portfolio of 0.59 for the minimum-variance portfolio, the equal-risk contribution portfolio has a Sharpe ratio of 0.46.

It is worth noting that the lower Sharpe ratio for the equal-risk contribution portfolio represents the price of lower asset concentration. More specifically, it represents the tradeoff between risk and concentration. The equal-weighted portfolio in which all of the four assets considered have the same weight of 25% has a portfolio return of 8.75%. Its variance is 0.9%, yielding a Sharpe ratio of 0.40.

The efficient frontier with the risk-free asset (the rate on three-month U.S. Treasury bills) is illustrated in Figure 2. The slope of the red line measures the reward-to-risk ratio of the portfolio without farmland, whereas the blue line measures the reward-to-risk ratio of the portfolio with farmland. The slope of the blue line is 7.14, which is much greater than the slope of the red line (2.07). The difference of 5.07 indicates the improvement of portfolio performance resulting from the addition of farmland to the baseline portfolio. This confirms the attractiveness of farmland investment from a portfolio perspective.

In summary, previous results suggest two interesting points. First, farmland investment is more attractive when considered in a portfolio than when considered in isolation from other investments. Second, portfolios incorporating farmland have better performance than portfolios without farmland.

CONCLUSIONS

The data we examined in this paper provides support of how farmland investment fits into a diversified portfolio of U.S. stocks and bonds, REIT, three-month Treasury bills, and gold. Farmland was found to be a good diversifier of risk in a traditional portfolio, as well as having a dominant weight in MV, minimum-variance, and equal-risk contribution portfolio strategies. Our results confirm findings in Lins, Sherrick, and Venigalla (1992), which covered 1967–1988. Previous literature shows that the ranking of portfolio selection strategies is not unique in the sense that there is a portfolio selection strategy that dominates other strategies. Which strategy dominates depends on the tradeoff between concentration and the Sharpe ratio. In this study, the minimum-variance portfolio had a higher Sharpe ratio than the equal-risk contribution portfolio.

Our findings help explain two trends associated with farmland investments. First, there has been an increased interest by institutional investments in farmland. This trend became obvious following the large increase in crop prices in 2007, along with the 2008 housing bubble and the financial recession (Fairbairn, 2014). The second trend is the emergence of the farmland REIT in 2013 by Gladstone Land Corporation followed by Farmland Partners in 2014. These trends suggest that farmland has attractive return-risk characteristics.

One limitation of this study is that we did not consider the issues of farmland liquidity and transaction costs. Indeed, the direct transaction cost involved in the transfer of farmland ownership is nontrivial. Looking at studies that estimated farmland transaction costs, such as Moyer and Daugherty (1982) and Wunderlich (1989), the transaction cost for U.S. farmland ownership ranges from a low of 5% to a high of 15% of farmland purchase price. Although the estimation and incorporation of transaction cost in the portfolio selection problem would be computationally demanding, it could potentially have a significant impact on optimal allocation. Nevertheless, it is commonly accepted that relying on low-frequency data like ours over a relatively long period helps mitigate the impact of transaction costs.

In addition to transaction costs, we did not examine after-tax returns. The tax treatment for farmland differs from that of other capital assets. In addition, there are significant differences in the rates of property taxes from one state to another. For instance, property taxes in California are much higher than property taxes in Indiana. Another limitation is that farmland management has critical operational details that were not considered in this study. Of course, management of farmland has a critical impact on its risk-return characteristics. Therefore, farmland risk-return is endogenous to farmers' effort and management capabilities. This study, along with other farmland portfolio diversification studies, looks at the risk-return characteristics of asset classes as exogenous to the portfolio selection model.

FOOTNOTES

[1] Like the majority of theory papers, Markowitz's (1952) focus was on the theoretical foundation of the MV model and not on econometric issues such as problems of aggregation of individual assets into one asset class.

[2] The most conspicuous example of institutional interest in farmland investing is the $2 billion investment in farmland by the giant pension fund Teachers Insurance and Annuity Association-College Retirement Equities Fund (TIAA-CREF) in 2010.

[3] CRSP is an affiliate of the University of Chicago Booth School of Business. http://www.crsp.com.

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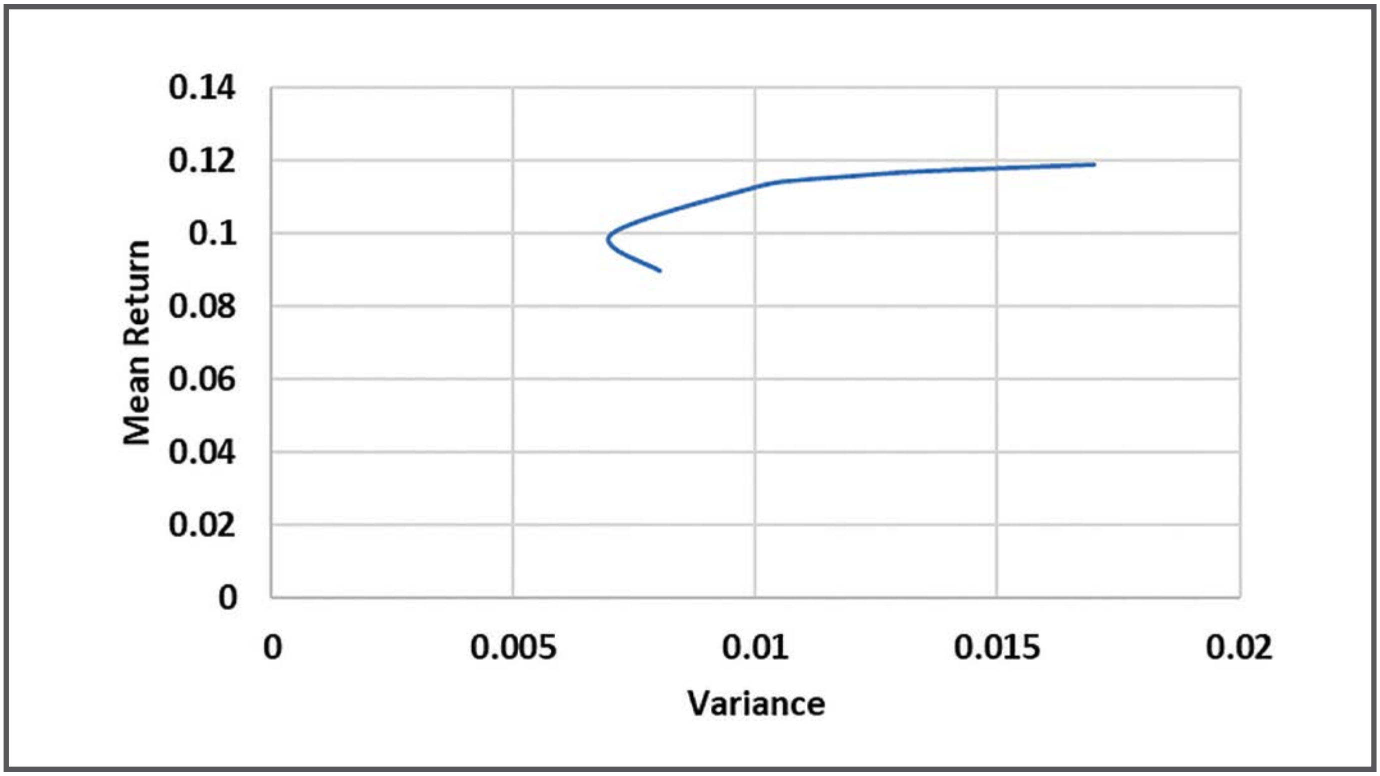

Figure 1. Efficient Frontier without Risk-Free Asset, 1973–2017

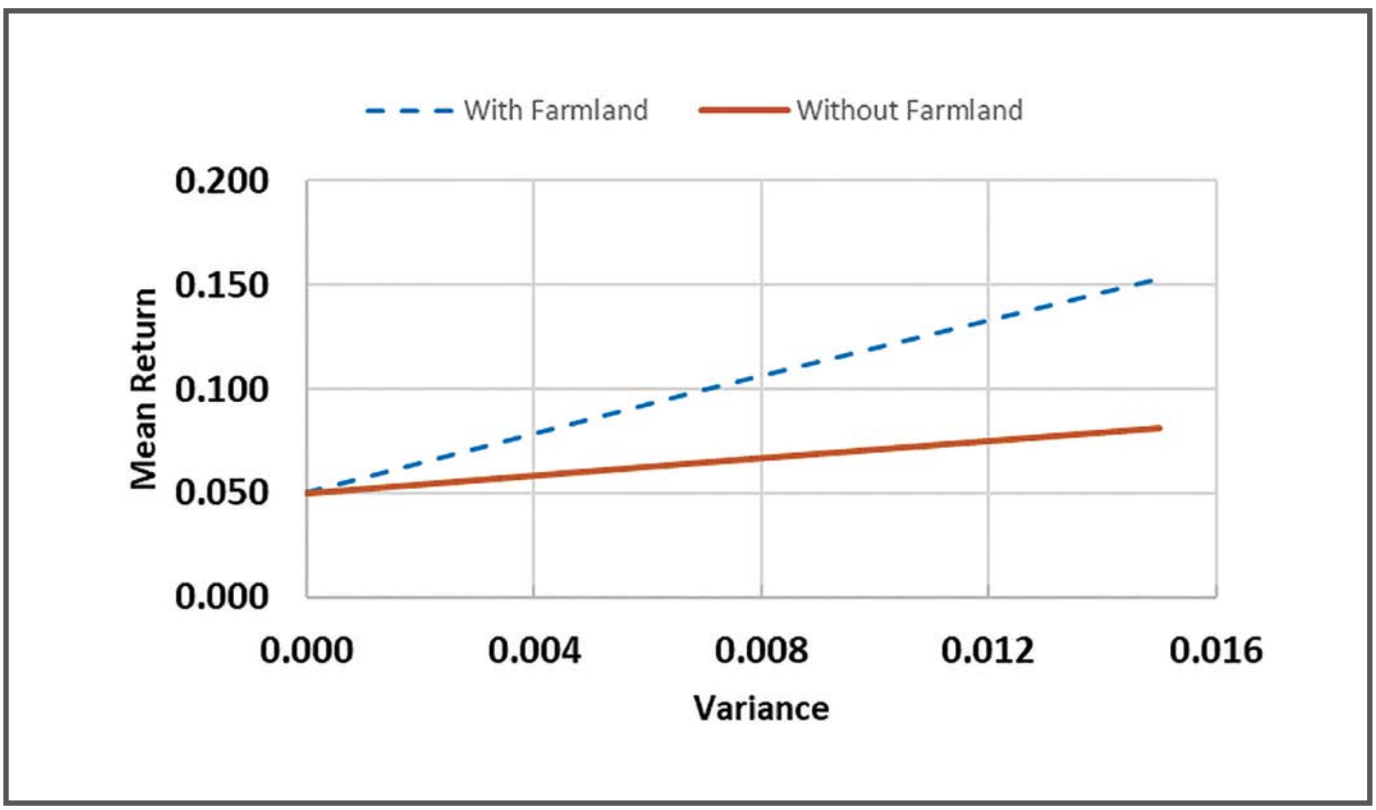

Figure 2. Efficient Frontier with Risk-Free Asset: With and Without Farmland, 1973–2017

Table 1. Descriptive Statistics, 1973–2017					
Annual Return	**S&P 500**	**Gold**	**REIT**	**3-Month T-Bill**	**Farmland**
Mean	0.097	0.083	0.046	0.047	0.121
Std. Dev.	0.184	0.258	0.168	0.035	0.135
Variance	0.031	0.057	0.035	0.001	0.019
Min	−0.385	−0.310	−0.496	0.000	−0.150
Max	0.659	1.173	0.365	0.140	0.572

Table 2. Correlation and Covariance Matrices				
Correlation Matrix				
	S&P 500	**Gold**	**REIT**	**Farmland**
S&P 500	1.00			
Gold	−0.12	1.00		
REIT	0.39	−0.06	1.00	
Farmland	−0.21	−0.01	−0.05	1.00
Covariance Matrix				
	S&P 500	**Gold**	**REIT**	**Farmland**
S&P 500	0.034			
Gold	−0.006	0.067		
REIT	0.013	0.003	0.035	
Farmland	−0.005	−0.000	−0.001	0.019

Table 3. Equal-Risk Contribution Portfolio, 1973–2017				
	Portfolio Weight	**Volatility**	**Risk Contribution**	**Risk Weight**
S&P 500	24.2%	18.0%	6.5%	25.0%
Gold	16.5%	24.5%	6.5%	25.0%
REIT	25.7%	17.0%	6.5%	25.0%
Farmland	33.6%	13.0%	6.5%	25.0%
Total	100.0%	17.5%	26.0%	25.0%

Self-Perceived Economic Hardship Versus Financial Measures Influence on Farmer Well-Being

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Abstract

Farmer stress and well-being are current issues of concern. In addition to social stressors, the recent distressed farm economy has increased financial stress for many farmers. This non-experimental, correlational study measured how farm finances influenced emotional well-being in adult farm business management (FBM) and post-secondary (PS) production agriculture students in Minnesota. A total of 260 participants responded to a questionnaire on farm finances and well-being, as measured by the emotional health subscales from the RAND 36-Item Short Form Health Survey (SF-36). On average, respondents did not have significantly different emotional well-being than the general population. However, financial status significantly predicted lower emotional well-being in the respondents.

INTRODUCTION

The U.S. Centers for Disease Control reported that 54 farmers, ranchers, and other agricultural managers committed suicide during 2015, the most recent year of data (Peterson et al., 2018). Social isolation, stressful work environments, and lack of access to healthcare may lead farmers to be high risk for mental health issues including suicide (Tiesman et al., 2015). In addition to those factors, the overall distressed production agricultural economy has recently reduced farm-level profitability, liquidity, and solvency, increasing stress for many agricultural producers. The United States Department of Agriculture's (USDA's) Economic Research Service found 2018 to have the lowest net farm income since 2006 (2018b). Those working with farmers and ranchers, such as appraisers, farm managers, educators, and other service providers, can benefit from building awareness of how agricultural financial stress affects farmers' personal well-being.

Prior to this study, there was no current data on emotional well-being during challenging financial periods collected directly from Minnesota farmers and future farmers. There was particular interest in studying these issues in a specific subset of Minnesota farmers. In Minnesota, farm business management (FBM) students/participants are farm owners, farm operators, or those interested in farming as an occupation; adult participants enroll in tuition-based credits at a Minnesota State Colleges and Universities (Minnesota State) two-year institution (AgCentric, 2018). Adult FBM participants receive educational input of farm management topics from FBM instructors in one-on-one settings (Southern Minnesota Center of Agriculture, 2018). While the term "student" is used in the Minnesota FBM program, the association between FBM instructors and FBM students could also be described as a farm financial consultant and client relationship. All FBM participants are 18 or older, but because FBM participants are farming either full-time or part-time, their average age is typically older.

Minnesota State also offers production agricultural two-year degrees in classroom-based campus settings for post-secondary (PS) students. In this study, a PS student was defined operationally as a student enrolled in a post high school two-year degree, two-year diploma, or one-year certificate program. Due to the population parameters, all PS student respondents in this study were enrolled in a Minnesota State agricultural production program. Minnesota State agricultural production students plan to pursue careers in farming, either as a producer or as a farm worker. They also typically have direct farming experience, having grown up on a farm, worked on a farm, and/or already started farming as a primary or secondary operator.

The purpose of this study was to quantitatively measure economic factors, including self-perceived financial hardship and self-reported farm financial measures, as well as those factors' influence on current emotional well-being in a target population of Minnesota adult FBM participants and agricultural production PS students. The following research questions guided this study:

1. Does self-perceived economic hardship predict decreased levels of emotional well-being?

2. Do weaker farm financial measures predict decreased levels of emotional well-being?

PREVIOUS RESEARCH

In the late 1980s and throughout the 1990s, the aftermath of the "farm crisis"—a period of extreme economic recession in U.S. agriculture beginning in 1982 (FDIC, 1997)—caused an influx in research on farmers' emotional well-being. Among agricultural populations in the 1980s, researchers found low levels of emotional well-being, operationalized as increased anxiety, depression, alcohol and drug usage, domestic violence, and other behavioral health concerns (Bultena, Lasley, and Geller, 1986; Davis-Brown and Salamon, 1988; Hargrove, 1986; Heffernan and Heffernan, 1986; Walker and Walker, 1987; Weigel and Weigel, 1987).

Financial stressors, in particular farm debt, were factors linked to increased farmer stress (Keating, Doherty, and Munro, 1986). Armstrong and Schulman (1990) studied depression, financial strain, and perceived personal control, finding that self-perceived household economic hardship was a statistically significant positive predictor of depression, whereas debt-to-asset ratio, an objective measure of farm financial solvency, was not. Marotz-Baden (1988) found that lower income and lower economic satisfaction correlated with stress, particularly for older generation farmers and their farming sons. In the decade after the farm crisis, Hoyt et al. (1997) found that some rural residents hold stigmatized views related to seeking mental health, and financially challenged rural residents may be at significant risk because "personal economic hardship is consistently found to be related to physiological distress" (449–450).

Internationally, there has been more recent research on farmer stress—for example, Finnish dairy farmers (Kallioniemi et al., 2016), European and Australian dairy farmers (Kolstrup et al., 2013), and stress and well-being of Australian farmers with hearing impairment (Hogan et al., 2015). Canadian farmers' "scores for stress, anxiety, and depression were higher, and resilience lower, than reported normative data" (Jones-Bitton et al., 2019, 1). Fraser et al. (2005) found 45 articles on farmer mental health and stress in a comprehensive literature review of published research on farmer mental health from 1985–2005. The term "emotional well-being" was not used by researchers in Fraser et al.'s (2005) literature review, although well-being was a term utilized by other researchers, such as Armstrong and Schulman (1990).

In Minnesota, the geographic focus of this study, a Minnesota Department of Agriculture convenience sample survey of agricultural professionals and law enforcement professionals showed that respondents observed depression, anxiety, and stress in farmers (Moynihan, 2017). The Moynihan (2017) study suggested that farmer emotional well-being was a relevant and concerning problem in Minnesota. Policy decisions at the national level also support the relevance of the issue. The 2018 Farm Bill included $10 million annually for increased federal funding to state departments of agriculture, a cooperative extension service, qualified non-profits, and other appropriate entities to provide services to farmers and ranchers in crisis through a Farm and Ranch Stress Assistance Network (Agricultural Improvement Act, 2018).

METHODS

This non-experimental, quantitative correlational study used survey research methodology and was part of a larger project by Roberts (2019). Survey design enabled both descriptive and inferential statistical analysis of the data (Fraenkel, Wallen, and Hyun, 2012). In the target population, this study determined relationships between emotional well-being, self-perceived economic hardship, self-reported farm financial measures, and select demographic data. An online anonymous Farmer Well-Being Questionnaire, developed for this study, collected data from respondents. Respondents self-identified differences in the variables through their answers on the questionnaire; there was no experimental manipulation of variables. Respondents could participate in the survey between April 1, 2018, and October 1, 2018. Institution Review Board approval was obtained through Minnesota State's South Central College.

Population

The target population was comprised of two subsets, PS students (n = 223) and FBM participants (n = 2,197) at two-year colleges represented by Minnesota State Centers of Excellence in Agriculture. There were 2,420 possible respondents (223 PS students population subset + 2,197 FBM participants population subset = total population N of 2,420). The targeted participants represented a non-probability purposive population (Fraenke, Wallen, and Hyun, 2012). Total respondents, n = 260, at the conclusion of the data collection resulted in a response rate of 10.7%.[1]

Respondents represented a variety of ages, farm types, and experience levels. Participants were directly involved in production agriculture (i.e., farming) at full- or part-time levels (Southern Minnesota Center of Agriculture, 2018). FBM participants were 158 of the respondents, PS students were 66 of the respondents, and 36 did not identify whether they were FBM or PS. Of respondents that answered demographic questions, age (n = 174) ranged from 17–76, with a mean of 38 years old, median of 36, and mode of 18. FBM participants had a mean age of 43, while unsurprisingly PS students were on average younger, with a mean age of 25. Gender (n = 236) selected by respondents were male (n = 186, 78.81%), female (n = 47, 19.92%), prefer not to say (n = 2, 0.85%), and other (n = 1, 0.42%). Race/ethnicity of respondents (n = 236) was overwhelmingly white (n = 227, 96.61%).

Instrumentation

A panel of experts (university faculty members and administrators in agricultural business management and extension education) reviewed the questionnaire for content validity before it was sent to respondents. Emotional well-being was measured using pre-established emotional- and mental-health questions excerpted from the RAND 36-Item Short Form Health Survey (SF-36). The SF-36 is based on decades of prior research in self-perceived mental and physical health (Stewart et al., 1992). The SF-36 is widely used and found to be a relatively stable and reliable metric in both ill and healthy populations; however, there are limitations to the instrument (Obidoa, Reisine, and Cherniack, 2010). For example, past research has shown that caution should be used when comparing across genders and age groups, as well as when using with healthy populations (ibid.).

In this study, there were 14 questions used from the SF-36. The scales used from the SF-36 were the (i) role functioning limitations due to emotional problems scale, (ii) energy/fatigue scale, (iii) emotional well-being scale, and (iv) social functioning scale. The SF-36 has known general population means, standard deviations, and reliability alphas for each scale (Stewart et al., 1992) (Table 1). Coding of the SF-36 converted questions to scores ranging from 0–100. After coding, lower scores represented poorer emotional health and higher scores represented better health (ibid.). For example, previous research has shown that individuals with depression and major depression score lower on the SF-36 mental health scales than respondents without those conditions (Hays, Sherbourne, and Mazel, 1995).

Farm finances and personal economics were also addressed in the Farmer Well-Being Questionnaire. Two self-perceived economic hardship questions were used from the Americans' Changing Lives survey (House, 2018). These personal finance questions were deemed reliable and valid in research (ibid.) similar to the purposes of this research. To contrast the self-perceived subjective financial hardship questions, three objective farm financial measures were included. Open-ended questions asked respondents to enter their debt-to-asset ratio, current ratio, and net farm income. Debt-to-asset ratio is a valid measure of solvency, current ratio is a valid measure of liquidity, and net farm income is a valid measure of profitability (Becker et al., 2014). Solvency, liquidity, and profitability are the three categories of financial ratio analysis and are accepted as uniform and objective measures of agricultural finances by the Farm Financial Standards Council and the USDA Economic Research Service (USDA ERS, 2018a).

The 2017 farm financial measures for the entire FBM population in Minnesota were published in the public FINBIN online database (Center for Farm Financial Management, 2018). This data was collected from January through March 2018 from a true census of Minnesota FBM participants (N = 2,306) participating in FINBIN. Known population figures for the financial measures for the FBM participants subset enabled a comparison of the farm financial questions responses submitted in the Farmer Well-Being Questionnaire to the results from the statewide FBM census. To determine if the mean financial ratios from the Farmer Well-Being Questionnaire FBM respondents, x, was significantly different from the mean financial ratios from the known FBM population, μ, one-sample t-tests were conducted.

The null hypotheses were H_o: $\mu_k = x_k$, that the sample mean is equal to the known population mean (i.e., the 2017 FINBIN averages published in May 2018). The respondents' debt-to-asset ratio mean was 42% or 0.42 (SD = 0.193), while the FINBIN ratio was 44% or 0.44 (SD = not reported), (t = –0.22, p = 0.83). The respondents' current ratio mean was 2.87 (SD = 4.85), while the FINBIN ratio was 1.60 (SD = not reported), (t = 1.97, p = 0.05). The respondents' net profit mean was $19,013 ($SD$ = $295,111), while the FINBIN mean was $62,005 ($SD$ = not reported), (t = –1.30, p = 0.20). All null hypotheses failed to be rejected ($p \geq 0.05$). These analyses showed that the survey respondents' reported financial measures were not significantly different from the total Minnesota FBM population (Table 2).

Analysis

Qualtrics data, downloaded into Excel, was shared by the third-party survey administrator on January 2, 2019. Data was sorted, cleaned, and recoded in Excel. Data was then uploaded to the IBM SPSS Statistics platform (version 24.0). Descriptive statistics were conducted for all research questions. For non-parametric and inferential statistical analysis, all procedures, unless specifically noted, followed protocols outlined by Field (2015). The alpha level was set at 0.05 *a priori* for all non-parametric and inferential analyses.

Research question one—does self-perceived economic hardship predict decreased levels of emotional well-being—was measured using simple linear regression following the protocol outlined in Field (2015). Emotional well-being, the interval level dependent variable, was measured as the summation of the four RAND SF-36 scales in the survey divided by four (possible range 0–100). The independent interval variable was self-perceived economic hardship, which is the summed scores of the two Likert questions on subjective financial state (possible range 2–10). The magnitude of correlations was measured using Davis's (1971) conventions. Cohen's f was calculated for effect of the omnibus model, and effect magnitude was interpreted using Cohen (1988). The standardized beta was reported to indicate the importance of the model predictor (Field, 2015).

The omnibus null hypothesis assumed there was no statistically significant relationship between self-perceived economic hardship and economic well-being (H_o: $R^2 = 0$). The alternative hypothesis assumed there was a statistically significant relationship between self-perceived economic hardship and economic well-being (H_a: $R^2 \neq 0$). The follow-up hypothesis states that the beta was not statistically different from zero (H_o: $\beta_1 = 0$), while the alternative hypothesis states that the beta for self-perceived economic hardship was statistically different from zero (H_a: $\beta_1 \neq 0$).

Research question two—do weaker farm financial measures predict decreased levels of emotional well-being—was measured using multiple linear regression as outlined in Field (2015). Emotional well-being, the interval-level dependent variable, was measured as the sum of the four RAND SF-36 scales divided by four. The independent ratio variables were 2017 debt-to-asset ratio, 2017 current ratio, and 2017 net farm income. Cohen's f was calculated for effect of the omnibus model, and effect magnitude was interpreted using Cohen (1988). The standardized betas were reported to indicate the importance of the model predictors (Field, 2015).

The omnibus null hypothesis assumed there was no statistically significant relationship between farm-level economic data and economic well-being (H_o: $R^2 = 0$). The alternative hypothesis assumed there was a statistically significant relationship between self-perceived economic hardship and economic well-being (H_a: $R^2 \neq 0$). The follow-up hypotheses state that each beta—2017 debt-to-asset ratio, 2017 current ratio, and 2017 net farm income—was not statistically different from zero (H_o: $\beta_k = 0$), while the alternative hypotheses state that each beta was statistically different from zero, (H_a: $\beta_k \neq 0$).

RESULTS

The overall emotional well-being scale used a summation of the four individual subscales from the SF-36. Although the results of the respondents' emotional well-being are not the focus of this article, respondents' means and standard deviations for each subscale and the overall emotional well-being average scale are displayed in Table 3. This overall emotional well-being average scale is the dependent variable in both research questions.

Emotional Well-Being and Self-Perceived Economic Hardship

The mean overall emotional well-being average for respondents (n = 251) who answered the subjective financial questions was 64.65 (SD = 20.69). The mean subjective financial scale was 6.71 (SD = 2.26) (Table 4). The emotional well-being average was positively correlated, at a statistically significant level, with respondents' subjective financial scale (r = 0.63, p < 0.01). The magnitude of the correlation was substantial (Davis, 1971).

The overall emotional well-being scales average regressed on the subjective financial hardship scale had an R^2 = 0.40, $F(1,250)$ = 165.77, p < 0.01 (Table 5). The regression[2] explained 40% of the variance in emotional well-being data. Cohen's f was 0.82, a large effect size (Cohen, 1988). The results of the regression were statistically significant at the 0.05 level, and the null hypothesis was rejected. Subjective financial data statistically significantly predicted emotional well-being in the respondents. The subjective financial scale coefficient was 5.78 (t = 12.88, p < 0.01). The standardized beta coefficient was 0.63. The beta null hypothesis was rejected and the alternative hypothesis was accepted as true. One unit of increased subjective financial scale increased the average emotional well-being scale score by 5.78 units, *cetaris paribus*. The regression equation was

$$\textit{Emotional Well-Being}_i = 25.85 + 5.78\ \textit{Subjective Financial Hardship}_i$$

where 25.85 = $\widehat{\beta_0}$ (i.e., the constant) and 5.78 = $\widehat{\beta_1}$.

Emotional Well-Being and Farm Financial Measures

The mean overall emotional well-being average for respondents (n = 52) who entered their farm-level solvency, liquidity, and profitability financial measures was 62.68 (SD = 21.30). The debt-to-asset ratio mean was 41.7% or 0.4172 (SD = 0.193), the current ratio mean was 2.99 (SD = 5.06), and the net profit mean was $58,608.77 ($SD$ = $201,556.67) (Table 6). The emotional well-being average was significantly correlated with respondents' debt-to-asset ratio (r = –0.37, p = 0.01, moderate association), current ratio (r = 0.26, p = 0.03, low association), and net profit (r = 0.29, p = 0.02, low association) (Davis, 1971) (Table 7).

The overall emotional well-being scales average regressed on farm debt-to-asset ratio, current ratio, and net profit had an R^2 = 0.185, $F(3, 51)$ = 3.631, p = 0.019 (Table 8). The regression[3] explained 18.5% of the variance in the emotional well-being data. Cohen's f was 0.48, a medium effect size (Cohen, 1988). Results of the regression are statistically significant at the 0.05 level, and the null hypothesis was rejected. Farm financial data statistically significantly predicted emotional well-being in the respondents. However, the individual t-values of the beta coefficients were not statistically significant for any of the three variables. The standardized beta coefficients were –0.25 for debt-to-asset ratio, 0.12 for current ratio, and 0.22 for net farm income. The follow-up null hypotheses failed to be rejected. Due to the lack of significance of the beta coefficients, a regression equation was not developed or reported for this research equation.

CONCLUSION

The emotional well-being scales average regressed on the subjective financial hardship scale were statistically significant and explained 40% of the variance in emotional well-being data. While the results corroborated the findings of previous studies (e.g., Armstrong and Schulman (1990) and Marotz-Baden (1988), there are some limitations to these findings. The self-perceived financial hardship questions had not been used previously in a study with agricultural respondents. Furthermore, the self-perceived hardship scale was based solely on two questions.

The emotional well-being average had the largest correlation with respondents' debt-to-asset ratio (r = –0.369, p = 0.004, moderate association), which supported Keating, Doherty, and Munro's (1986) study of farmers during the Farm Crisis of the 1980s. Further analysis showed that the overall emotional well-being scales average regressed on farm debt-to-asset ratio, current ratio, and net profit was statistically significant, but only explained 18.5% of the variance in emotional well-being data. No individual betas were statistically significant, leading to a lack of applicable experimental regression equation.

In comparison to self-perceived economic hardship's relationship with farmer well-being, objective farm financial measures had a weaker relationship with farmer well-being and explained less variance. The effect size was also lower. In other words, how a respondent felt about their financial situation was a better predictor of emotional well-being than financial measures on the respondent's balance sheet, cash flow, and/or income statement. Subjective perceptions mattered more than objective measures in this analysis. However, less than a quarter of overall respondents (n = 260) responded to the farm financial measure questions (n = 52) in the Farmer Well-Being Questionnaire; the small n limits the analysis and its generalizability. Additionally, the small n to the farm financial measure questions may tell us something about how well respondents knew or did not know their farm financial measures. It is noteworthy that in a group primarily of farmers who have self-selected into continuing education on FBM, the majority chose not to report their farm financial measures. It is unknown if this was due to respondents not knowing the measures or due to not wanting to share them (even in an anonymous survey).

RECOMMENDATIONS

Minnesota FBM participants and PS students do not mirror the general population of farmers. I recommend additional research on the relationship between farm finances and emotional well-being with a general population of farmers. Random sampling within a population of farmers would improve generalizability of results. While the SF-36 emotional well-being scales are reliable and valid measures of emotional health, those scales do not address mental health disorders, such as depression or anxiety. There are several self-reported questionnaires that reliably and validly address mental health; two possible options include the Patient Heath Questionnaire-9 (PHQ-9) (Spitzer, 1999) and the Generalized Anxiety Disorder-7 (GAD-7) (Spitzer et al., 2006), which measure depression and anxiety, respectively. These questionnaires may be better suited to future research on the subject of emotional well-being and mental health than the SF-36.

Truchot and Andela (2018) recently developed "The Farmers Stressors Inventory" and identified a list of factors that cause burnout and hopelessness in farmers. These factors include "workload and lack of time, incertitude toward the future and the financial market, agricultural legislation pressure, social and geographical isolation, financial worry, conflicts with associates or family members, family succession of the farm, and unpredictable interference with farm work" (ibid., 859). This inventory may better assess farm-related stress than quantitative emotional well-being excerpts from the SF-36 included in this study. Furthermore, more qualitative research with farmers and/or agricultural students may better capture the nuances of the relationships between emotional well-being, finances, and other agricultural stressors.

There was a low *n* in this study for farm financial measure responses. This limited the results. Previous research is mixed in terms of how financial ratios affect emotional status in agricultural populations. A true census and improved data collection, such as correlating FBM participants' end-of-year financial analysis submissions to an emotional well-being measurement, might improve reliability and validity of this research question. Additional research is needed to determine how self-perceived financial hardship and farm financial measures differ in their effect on farmer emotional well-being. Furthermore, additional research is needed to determine how financial management skills and ability to calculate financial ratios affect well-being. The low *n* for the financial measure questions in this study suggests some lack of awareness of financial status even though this study's respondents were mostly FBM participants.

Current economic conditions will likely cause both financial and personal stress levels to continue to rise in agricultural communities. For farm management educators and consultants, this study increases awareness of the effects of farm financial challenges on farmers. The results of this study, while limited in overall generalizability, can help increase knowledge of how real and perceived farm financial hardships challenge farmers in more than economic contexts. Perceptions matter and may be more important at predicting emotional distress than actual financial measures. If agricultural education and service providers understand the influence of financial status, particularly a farmer's self-perception of their financial state, on emotional well-being, they may be better equipped to serve the needs of their students, participants, and/or clients.

FOOTNOTES

[1] Due to the low response rate, a comparison of emotional well-being scores of early and late respondents was conducted following procedures outlined by Lindner, Murphy, and Briers (2001). No significant difference ($p > 0.05$) was found between early and late respondents, indicating that responses were generalizable within the target population of this study and non-response error was likely minimal in this dataset (Lindner, Murphy, and Briers, 2001).

[2] Before interpreting the simple linear regression, tolerance values were checked for values under 0.2 (Menard, 1995) and variance inflation factors (VIFs) more than 10 (Myers, 1990). VIF was 1.00 and tolerance was 1.00. These collinearity statistics did not indicate issues of multicollinearity. The Durbin-Watson test was used to check the independence of errors; the value of 1.933 does not indicate interdependence of errors (Field, 2015).

[3] Before interpreting the multiple linear regression, tolerance values were checked for values under 0.2 (Menard, 1995) and variance inflation factors (VIFs) more than 10 (Myers, 1990). VIFs were 1.52 for debt-to-asset ratio, 1.40 for current ratio, and 1.10 for net profit. Tolerance statistics were 0.66 for debt-to-asset ratio, 0.72 for current ratio, and 0.91 for net profit. These collinearity statistics did not indicate issues of multicollinearity. The Durbin-Watson test was used to check the independence of errors; the value of 2.14 did not indicate interdependence of errors (Field, 2015).

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Table 1. Reliability, Central Tendency, and Variability of Emotional Scales in the RAND 36-Item Short Form Health Survey (SF-36)

Scale	Questionnaire Items	α	Mean	Standard Deviation
Role functioning/emotional	3	0.83	65.78	40.71
Energy/fatigue	4	0.86	52.15	22.39
Emotional well-being	5	0.90	70.38	21.97
Social functioning	2	0.85	78.77	25.43

Note: Results from baseline of the Medical Outcomes Study (N = 2,471). Adapted from "36-Item Short Form Survey (SF-36) Scoring Instructions," by RAND Corporation, 2018; retrieved from https://www.rand.org/health/surveys_tools/mos/36-item-short-form/scoring.html. Copyright 1994–2018 by the RAND Corporation.

Table 2. Comparison of FINBIN's Total FBM Student Population (N =2,369) Financial Ratios to Farmer Well-Being Questionnaire Respondents' Financial Ratios

Financial Ratio	Population μ	Respondent x	t	p
Debt-to-asset ratio (n = 65)	44%	42%	–0.22	0.83
Current ratio (n = 57)	1.6	2.87	1.97	0.05
Net farm income (n = 79)	$62,005	$19,013	-1.3	0.2

Note: Total population figures adapted from FINBIN database, Center for Farm Financial Management. Copyright 2018 University of Minnesota. Decimals on debt-to-asset ratio and net farm income not included in this comparison because the FINBIN database did not include decimals.

Table 3. Means and Standard Deviations of SF-36 Emotional Scales (n = 260)

Scale	Mean	Standard Deviation
Role functioning/emotional (n = 260)	61.54	36.58
Energy/fatigue (n = 257)	50.98	21.16
Emotional well-being (n = 256)	68.79	18.07
Social functioning (n = 259)	76.47	24.04
Overall emotional well-being average (n = 256)	70.17	20.81

Note: Scales range from 0–100, with lower scores indicating poorer emotional health and higher scores indicating better emotional health.

Table 4. Means and Standard Deviations for Subjective Financial Measures (n = 258)		
Variable	**Mean**	**Standard Deviation**
Satisfied with Family's Financial Situation[a] (n = 258)	2.97	1.14
Ability to Pay Monthly Bills[a] (n = 258)	3.72	1.27
Sum of Subjective Scale[b] (n = 251)	6.71	2.26

Note: n varies due to non-response; n for sum of subjective scale only includes respondents who also had an average emotional well-being scale score; mean emotional well-being scale score for these respondents 64.65 (SD = 20.69). [a]Coded 1–5, with 1 indicating financial hardship and 5 indicating no financial hardship. [b]Scale ranged from 2–10, with 2 indicating financial hardship and 10 indicating no financial hardship.

Table 5. Regression of Overall Emotional Well-Being Scales Average on Subjective Financial Scale (n = 251)					
Variable	B	$SE\ B$	b	t	p
Constant (b)	25.85	3.18		8.13	<0.01*
Subjective Finances (x_1)	5.78	0.45	0.63	12.88	<0.01*

Note: R^2 = 0.40, F(1,250) =165.77, p < 0.01*; * signifies p < 0.05.

Table 6. Means and Standard Deviations for Objective Farm Financial Measures (n = 52)		
Variable	**Mean**	**Standard Deviation**
Debt-to-Asset Ratio	0.42	0.19
Current Ratio	2.98	5.06
Net Profit	$58,608.77	$201,556.67

Note: The mean overall emotional well-being average for respondents who entered their farm-level solvency, liquidity, and profitability data was 62.68 (SD = 21.30).

Table 7. Objective Farm Financial Measures Correlations[a] with Overall Emotional Well-Being Scales Average (n = 52)			
Variable	r	p	*Magnitude*[b]
Debt-to-Asset Ratio	–0.37	0.01*	Moderate
Current Ratio	0.26	0.03*	Low
Net Profit	0.29	0.02*	Low

[a]Correlations are Pearson's; [b]effect size associations are interpreted by Davis, 1971; * signifies p < 0.05.

Table 8. Regression of Overall Emotional Well-Being Scales Average on Farm Debt-to-Asset Ratio, Current Ratio, and Net Profit (n = 52)					
Variable	B	$SE\ B$	b	t	p
Constant (b)	71.07	9.26		7.68	<0.01*
Debt-to-Asset Ratio (x_1)	–26.94	17.68	–0.25	–1.52	0.13
Current Ratio (x_2)	0.5	0.65	0.12	0.78	0.44
Net Farm Income (x_3)	<0.01	<0.01	0.22	1.58	0.12

Note: R^2 = 0.185, F(3,51) =3.63, p = 0.019*; * signifies p < 0.05.

Corn Maze: Navigating Seed Corn Discounts

By Chad Fiechter and Jennifer Ifft

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Abstract

Most seed companies offer a variety of discounts and incentives in the pricing of their hybrid seed corn varieties. In this study we tabulate early cash payment, early financing, and volume discounts for multiple seed companies to create representative discounts from early fall through late spring. Using seed costs from extension crop budgets, we provide an example of the cost of different financing arrangements. Based on published discount schedules, we show that seed discounts can easily reach over 20% less with early cash payment and volume discounts. Cost savings are substantial with early season seed company provided financing, but traditional financing will cost less in most scenarios.

INTRODUCTION

In today's farm economy, it is important to get full value out of all input expenses. Seed, pesticides, fertilizer, and fuel are the major production expenses for crop farms. Many producers take advantage of early payment and other discounts offered by input suppliers. Seed and chemicals often have complex pricing, with a range of pre-payment discounts, volume discounts, rebates, and other incentives. On top of this, financing options are almost always available from the seed companies, with their own schedule of discounts and fees. Knowing the payoffs of different input purchase arrangements can help farms manage through tight profit margins.

This study considers seed corn purchase, which requires complex accounting for multiple factors that influence the final or actual cost. Typically, prices are not known until around Labor Day. Most seed companies offer discounts for early cash purchase beginning as early as September and declining to zero by early winter. Volume discounts are also common: Prices can lower substantially if you limit the number of companies you work with. Financing often is available, usually through Rabobank or John Deere Financial, from most seed companies. Furthermore, companies may offer a plethora of additional discounts: early delivery, new customer, growing customer, loyalty, multi-year commitment, and others.

The multiple dimensions of seed pricing are enough to make anyone's head spin. However, individual company discounts typically apply to all varieties of a specific crop—corn in our case. To provide some clarity, we devise representative early payment, volume, and financing schedules. These are based on actual schedules of over 10 seed companies but are designed to be broadly representative of the industry. Our goal is to provide a range of possible discounts to identify where cost savings are the highest. Once we have these representative schedules established, we will provide an example that compares seed company financing to lender financing. We use seed corn costs from extension crop budgets to provide an example of the magnitude of money at stake with seed corn purchase. We focus on corn, but our findings can be generalized to many other field crops.

METHODS

We intentionally do not discuss any firm-level discount schedules, as our analysis is not intended to disclose information from an individual seed company or provide critiques. Instead our objectives are to (1) show the hypothetical range of prices that could be paid for seed corn based on published discount schedules and (2) draw management implications for early payment, volume, and financing decisions. While discounts are not uniform, we did find mostly consistent patterns that we summarize in this article.

We would like to emphasize that we are providing a reasonable approximation for how the seed industry utilizes discounts as incentives for purchase. Each company has unique programs, and it would be unfair to compare only the nominal discounts in these simple categories. We tabulated the program deadlines and discount rates for over 10 different seed corn companies. To create a standard framework, we chose five key dates with intervals of a month and a half and averaged the discount rates of each company during this period. Using the interval averages, we then created our representative discount schedule. The variation in discount programs between companies is documented in Figure 1, which illustrates the discount rates and corresponding final dates when the discounts are offered. Each line represents a different seed company.

The volume discounts are tabulated similarly. Our base is no volume discount. An average seeding rate of 34,000 seeds per acre is used for the conversion between acres and units of seed corn. We used the threshold of 500 acres (212.5 units) of corn as a "medium volume discount." The "high volume discount" reflects a threshold of 2,000 or greater acres (850 units). This is often the top of the published volume discounts. Using our order size standardization, we then tabulated the volume discounts and calculated the average.

Table 1 shows early payment discounts with no volume discount, a medium volume discount, and a high volume discount. Discounts are all calculated from the "base" price, so we simply add together the early payment and volume discounts. Our dates of September 15, November 1, December 15, February 1, and March 15 are representative cutoff points; September 15 cutoff was the earliest we observed. Early payment discounts decline gradually in the fall but more rapidly in the winter. By mid-March, most companies no longer allow an early payment discount. For farms that buy seed in early fall and have some type of volume discount, only accounting for these two types of discounts, prices should be nearly 20% lower than the base. Zulauf and King (1985) find a 10% discount in seed price in their survey of Ohio farmers. This could represent a change in the practices of seed companies or the prevalence of larger farms today.

Most seed companies offer financing under a different discount schedule, which we summarize in Table 2. Locking in financing early and obtaining a volume discount can lead to discounts from the base price in the range of 15%, which still offers meaningful cost savings. Table 2 does not include interest costs. We found that interest costs for seed companies (often prime to prime plus 1%) are comparable to those being currently offered on operating lines from Farm Credit and commercial banks. However, there is a lower discount on the seed base price. Unless promotional financing is being offered and all else is held equal, the key difference between company and bank financing is the reduction in discount.

While the difference between early payment cash discount and early financing discount appears to narrow when comparing Tables 1 and 2, this is an artifact of averaging. If you look at an individual seed company, the difference between the early payment cash discount and the early financing discount is the same in each time period. We observe this distance to be close to 5% for most seed companies. This differential may help cover the costs companies pay to offer financing. Table 3 provides a hypothetical firm-level schedule to illustrate this point.

Our analysis does not directly account for different base prices being charged for specific varieties by seed companies. This data is largely considered confidential and is more difficult to access across a range of seed companies. Furthermore, the hypothetical discount range is still quite similar across firms, no matter the base price. After we establish a range of prices, we use average seed corn prices and seeding rates from Ohio State University crop budgets to give an example range of costs.

FINANCING CASE STUDY

Crop budgets for Ohio assume the average price of a bag of seed is $270[1] in 2019. This price likely reflects some existing degree of discounting or a combination of hybrid varieties selected with different base prices. The hybrid variety mix may be made up of one-third in the highest pricing tier, one-third in the middle pricing tier, and one-third in the lowest pricing tier. The corn enterprise of the farm may experience an average cost of $270 per bag (or unit) using this strategy. In Figure 1 we show the difference between the no discount price and the combined early payment cash and medium volume discounts. The difference would be greater in the case of the high volume discounts. We compare both early payment and early financing discounts with different financing options.

Figure 2 illustrates the cost advantage for a producer who can utilize the early payment cash discount through cash reserves or financing from a traditional lender. Our example base price of $114.75 is consistent with Schnitkey and Sellars's (2016) evaluation of price growth for crop inputs through time. The difference between the discounted price of the early payment cash discount and the early financing discount is more than $5. "Early Payment Cash Price: Operating Loan, Prime" and "Early Financing Price: Prime" reflect a simple amortization using the current *Wall Street Journal* prime rate of 5.25%.[2] We assume for all financing options the loaned funds will be carried the entire period and repaid in full on December 15. For comparison, some of the companies provide promotional financing with preferable rates. This scenario is illustrated by "Early Financing Price: Prime Minus 2%." With regard to promotional financing, only rates very close to 0% would provide a better price than using an operating loan from another lender for the payment of the early payment cash discount. For the early payment cash price, we should technically be including an opportunity cost of capital. However, given the current low interest rates on deposits, we do not make this adjustment in favor of simplicity and interpretability.

DISCUSSION AND CONCLUSION

Our strongest management takeaway is that procrastination may be costly. While many producers take advantage of early payment discounts, the decision has multiple components. If financing is needed, the terms are typically similar to lenders—and early discounts are still provided if the financing is locked in early. If a producer is aware of potential challenges with procuring financing, it would be beneficial to evaluate early while there is still time to take advantage of company provided financing. If a producer is not concerned about financing, it still seems prudent to seek communication with a loan officer to illustrate the potential opportunity surrounding early payment discounts. We believe that "intentionality" is rewarded in the relationship lending norm of the agricultural credit market. A clear representation of the potential gain of the early payment cash discounts may influence a lender to extend or increase an operating loan to experience the benefits presented.

Company provided promotional financing with more attractive interest rates than a producer's traditional lender may be a good option for some producers. Some companies may internally "subsidize" their financing programs. Company provided financing may be helpful for producers who have concerns about additional financing from their traditional lender. As discussed earlier, producers who have access to lending from their traditional lender would need to experience rates close to 0% to be better off. Any promotional interest rates should be evaluated in combination with all possible discounts and the base price offered by the seed company.

Our analysis does not consider base price and the assortment of other discounts available, which are also important for management decisions. Further, negotiation is always possible in nearly any business transaction. Given how simple it was to show a 20% differential relative to base price, it is not difficult to envisage the range reaching one-third, but this is beyond the scope of our analysis. Our analysis also does not consider incentives such as trips or merchandise, which may factor into some decisions. For operators who have trouble "spending money on themselves," such incentives may have meaningful non-cash value. A general understanding of the costs underlying the rewards may be a useful thought exercise as a grower seeks to understand the true price of their seed.

The seed corn industry has interesting supply chain challenges, as discussed in Jones et al. (2003). Hybrid seed corn must be grown in a previous season or in different geographic areas to ensure seed that can be sold and planted in a timely manner. Ultimately, seed corn inventory management is expensive. The practice of early payment discounts could be explained by the desire to lower inventory costs for seed companies.

Concern has been raised by Abendroth, Elmore, and Rouse (2006) to the possible yield gains sacrificed by a hurried decision on hybrid selection. We agree that a producer needs to be prudent in their selection of hybrids—the higher cost of high-yielding varieties will typically pay for itself. Often there are at least two or three years of commercial trials for most hybrids, so even new hybrids can be evaluated prior to the early payment discount period. Additionally, depending on the order flexibility of a seed corn company, the producer may still be able to make slight alterations to the hybrid variety mix after the initial selection.

We are motivated by the fact that discount schedules are a known value. In contrast, markets, weather, and politics are often out of control of individual producers—or products such as crop insurance must be purchased to mitigate the risk. By utilizing these seed corn discounts, a producer can reduce costs and help create some financial slack to minimize potential income shocks.

We do not believe discounts are an elaborate strategy to befuddle producers, but rather that they have become the industry norm of seed corn pricing. The maximum discounted price could be considered the base price, with premiums being charged for late purchase, seed delivery, etc. When viewed through the context of a premium instead of a discount, how would this change the attitude of producers? The strong industry competition highlighted in MacDonald (2017) should keep the pricing of seed corn competitive. Some firms, such as the Farmers Business Network, have begun to offer transparent pricing as a part of their business strategy. It will be interesting to see how the industry evolves over the next decade.

In our case study, we show that early seed corn procurement can easily lead to a $20 per acre differential, even without taking into account various other discounts and promotions. What is $20 per acre worth or equivalent to?

- Late season fungicide
- Buying a better hybrid
- Crop insurance premiums
- Staying at the lake while the Co-op sprays your fields

Our point here is that the potential savings from careful, early seed purchases are worthwhile. Early payment deadlines are pre-harvest (in a typical year) and it is understandable that producers will not have much bandwidth to make additional decisions during the thick of harvest. Hence, evaluating financing options and preparing for early payment well before harvest may be advisable.

FOOTNOTES

[1] Ohio State Crop Budgets, https://farmoffice.osu.edu/sites/aglaw/files/site-library/farmmgtpdf/enterprisebudgets/corn-con2019%20May2.xlsx.

[2] *Wall Street Journal* prime rate: 5.25% as of August 1, 2019.

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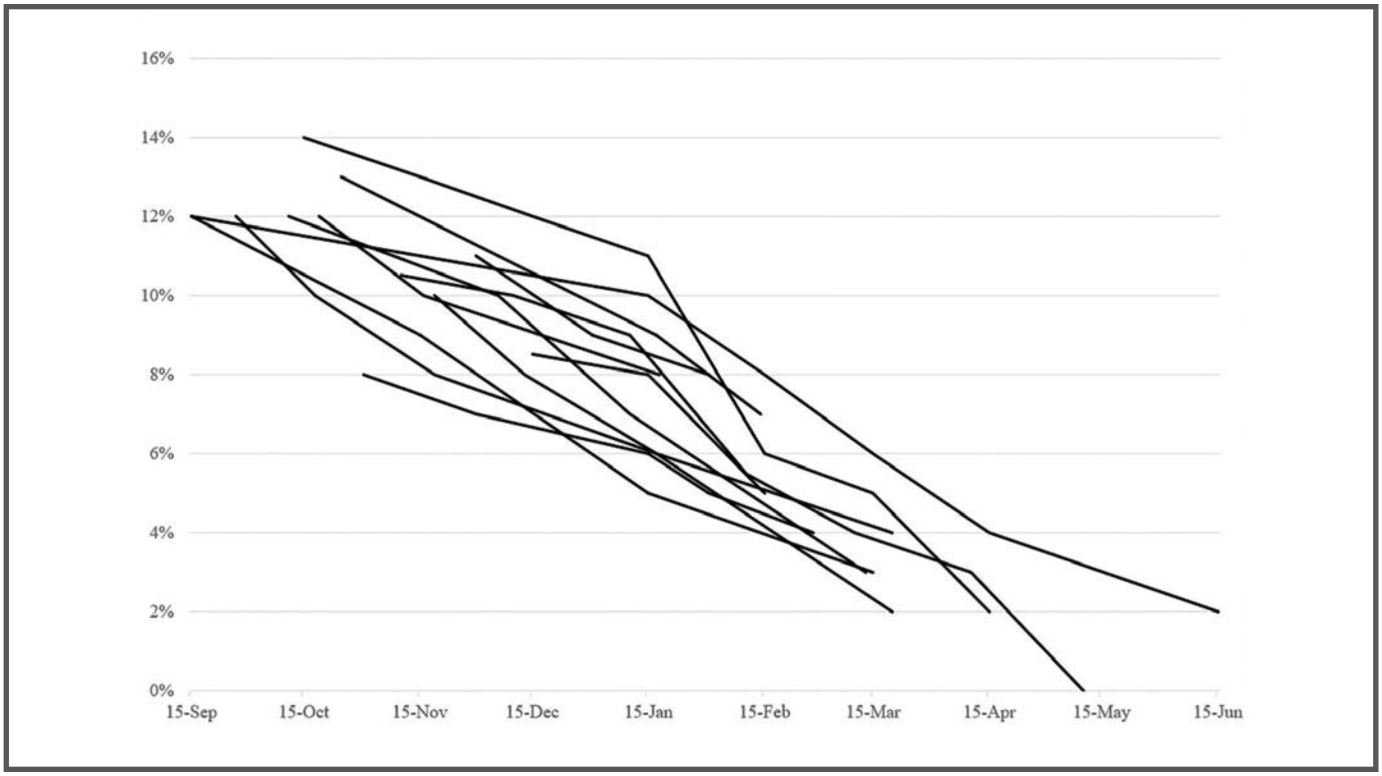


Figure 1. Early Payment Cash Discount by Seed Company (Note: Each line represents the actual discount schedule for seed corn offered by an individual firm or dealer.)

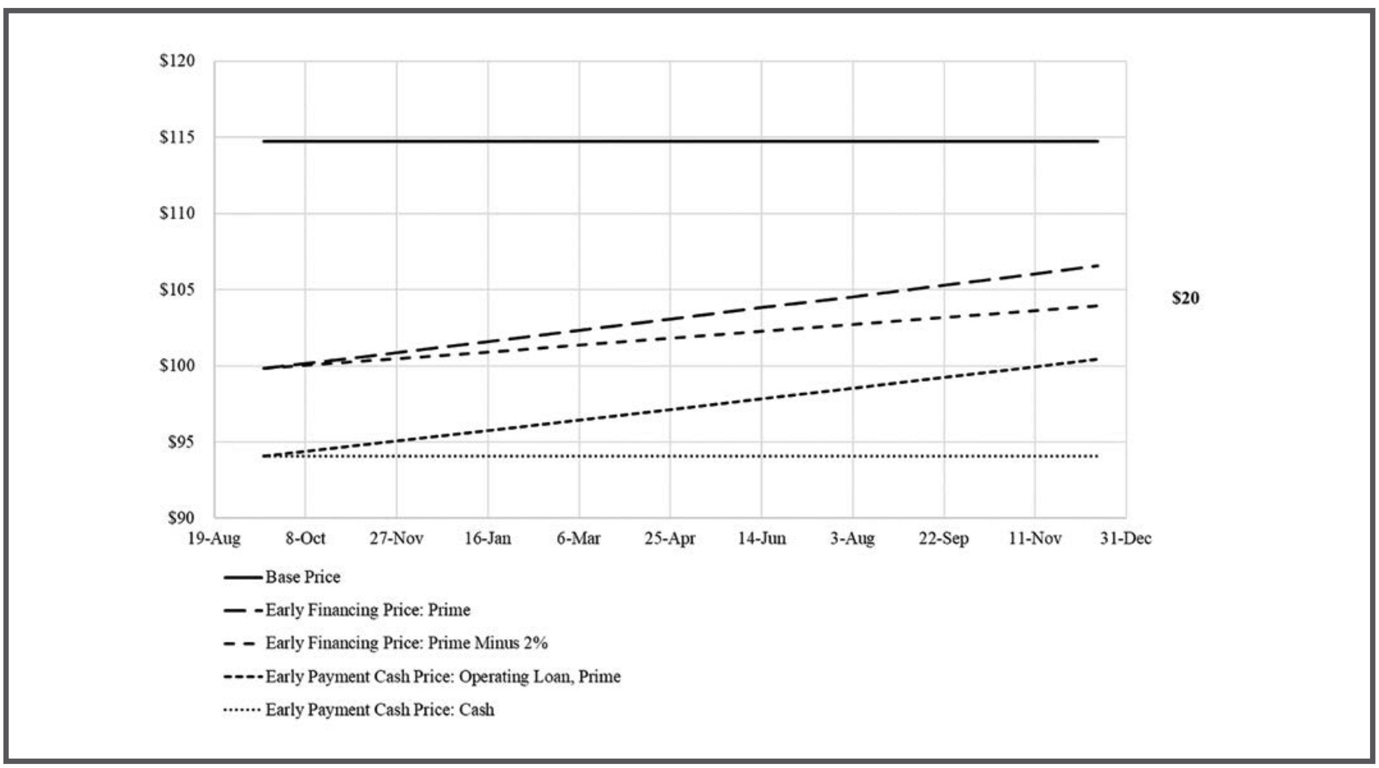


Figure 2. Per Acre Seed Corn Price with Financing Options (Note: We use the OSU Corn Crop Budget estimate of $270 per bag and a 34,000 seeds per acre seeding rate for the price per acre calculation. The Early Payment Cash Price is calculated with an early payment cash discount of 12% and volume discount of 6%. The Early Financing Price is calculated with an early financing discount of 7% and volume discount of 6%.)

Table 1. Seed Corn Discounts by Cash Payment Timing and Volume					
	15-Sep	**1-Nov**	**15-Dec**	**1-Feb**	**15-Mar**
Early Payment Cash Discount	12%	10%	8%	3%	0%
Medium Volume Discount	6%	6%	6%	6%	6%
Cash & Medium Volume	18%	16%	14%	9%	6%
High Volume Discount	9%	9%	9%	9%	9%
Cash & High Volume	21%	19%	17%	12%	9%

Note: Author calculations based on more than 10 individual seed company discount schedules. Assumes operator pays for seed with cash. Opportunity costs of paying in cash are not taken into account. Lender-financing interest costs are not included, as the observed seed company rates and lender rates are similar.

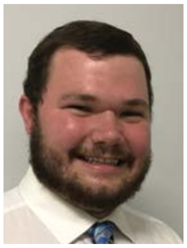
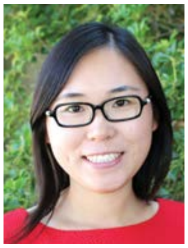
Table 2. Seed Corn Discounts by Financing Enrollment Date and Volume					
	15-Sep	**1-Nov**	**15-Dec**	**1-Feb**	**15-Mar**
Company Provided Financing Discount	7%	6%	4%	2%	0%
Medium Volume Discount	6%	6%	6%	6%	6%
Financing & Medium Volume	13%	12%	10%	8%	6%
High Volume Discount	9%	9%	9%	9%	9%
Financing & High Volume	16%	15%	13%	11%	9%

Note: Author calculations based on more than 10 individual seed company discount schedules. Interest costs are not included, as seed company and lender rates are similar.

Table 3. Hypothetical Seed Corn Company Discount Schedule					
	15-Sep	**1-Nov**	**15-Dec**	**1-Feb**	**15-Mar**
Early Payment Cash Discount	10%	8%	6%	3%	0%
Company Provided Financing Discount	5%	3%	1%	0%	0%

Note: Author calculations based on more than 10 individual seed company discount schedules. Interest costs are not included, as seed company and lender rates are similar.

Motivations and Challenges of Cover Crop Utilization for Georgia Crop Production

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Abstract

Georgia is the second largest producer of cotton and the largest producer of peanuts in the United States. These crops combined represent a significant portion of Georgia's economy. As natural resources become more threatened, the cotton and peanut industries have been facing increasing challenges to improve environmental sustainability. This research utilizes focus group interviews to identify the individual cost and revenue changes resulting from cover crop adoption, as well as the perceived benefits and challenges from changes in cultural practices that a farmer considers when adopting cover crops.

INTRODUCTION

Cover crops are known to yield numerous agricultural production benefits, as well as positive externalities and environmental benefits to society; however, little research has been conducted to explore the overall financial impact of utilizing cover crops for Georgia crop production. Culpepper et al. (2010) found that rye cover crop had the potential to reduce palmer amaranth emergence by 94% in the areas between rows in the field. Truman, Shaw, and Reeves (2005) demonstrated that cover crops in no-till conservation systems increased soil moisture infiltration by 54% compared to a conventional tillage without a cover crop treatment. Furthermore, cereal rye has been reported to collect from 20–100 pounds of nitrogen per acre, which can be utilized by the following summer crop (Gaskin, Cabrera, and Kissel, 2016). Reduced nitrogen leaching into groundwater is one of the most relevant environmental benefits of cover crop usage (Meisinger et al., 1991). Despite the potential on-farm and environmental benefits that cover crops can generate, the United States Department of Agriculture (USDA) 2017 Census of Agriculture reports that only 12% of harvested cropland in Georgia was planted with cover crops (USDA, 2019). This research will seek to identify and explore the individual costs and benefits associated with utilizing cover crops in cotton and peanut production systems.

This subdued rate of adoption can be traced back to the seemingly conflicting information regarding the economic benefits of cover crop adoption (Boyer et al., 2017). Cover crops can increase farm production costs and negatively impact crop yields. Producers might be concerned that implementing cover crops in their production practices might bring more economic uncertainties in their farming operations. This dilemma often results in producers relying entirely on conventional production practices.

Plastina et al. (2018a, 2018b, 2018c) examined the economics and motivations of cover crop use in corn and soybean production in the Midwest. Their findings aligned with previous research that insufficient familiarity with cover crops is a major barrier of adoption of cover crops (Nassauer et al., 2011). Plastina et al. (2018a) found that controlling soil erosion and improving soil health were the two most commonly stated benefits associated with cover crop adoption. Other benefits reported by focus group participants ranged from moderating risks to reducing farm production inputs. Furthermore, numerous costs and revenue changes were also reported by participants as a result of planting cover crops. Yield was a major budget revenue variable that farmers reported conflicting outcomes regarding the change they observe after planting a cover crop. However, partial budget results from a larger study indicated that adding cover crops to a production system often decreased net farm returns—except for farmers who utilize cover crops for winter grazing, who were typically able to increase their profitability (Plastina et al., 2018b, 2018c).

For Georgia row crop producers, limited research results are available in examining the comprehensive economic effects of cover crop usage for cotton and peanut production systems. As a result, most producers in Georgia chose not to adopt cover crops to avoid increasing the uncertainties from their farming operations. The goal of this study is two-fold. First, to inform growers, farm managers, and related professionals about the changes in costs and benefits faced by individual cotton and peanut growers who adopted winter cover crops in Georgia. Many of the aspects of these instruments that were necessary to be customized and updated were related to irrigation and moisture retention because supplemental irrigation is a larger consideration in the state of Georgia. Second, to explore farmers' motivations and obstacles to planting cover crops, as well as the variables farmers considered when making cover crop adoption decisions.

DATA

Based on the research methodology and survey instruments developed by Plastina et al. (2018a), this research investigated the cover crop adoption for Georgia's cotton and peanut production systems. Focus group interviews were conducted in four locations across Georgia with farmers who employ both conventional practices without cover crops and practices that incorporate winter cover crops into their production systems. The interviews were conducted from January 2019 to March 2019 in the Georgia cities of Sylvester, Vienna, Moultrie, and Waynesboro with cotton and peanut producers from seven Georgia counties in the central and southern portion of the state. In each interview location, two to six producers were interviewed. In total, 14 farmers participated in the focus group interviews. Two of the first questions asked during the focus group interviews were aimed at identifying the original and current motivations for utilizing cover crops. During the focus group discussions, farmers were asked general questions related to how the implementation of cover crops alters their production variables and their farm budgets. Questions related to how cover crop use impacts farm budgets were broken into the two categories of cost and revenue. Cost questions were designed to identify individual cost changes resulting from cover crop use, and revenue questions were intended to recognize revenue changes observed when farmers plant cover crops. Participants were also asked to describe some of their obstacles with cover crop usage and how they managed their winter cover crops. The consent form and questions presented to participants are included as Appendixes 1 and 2. The qualitative data collected through the farmer focus group interviews were carefully analyzed, and findings are summarized in the following section.

RESULTS

Cover crop management decisions varied from farm to farm, including the type of cover crop planted, termination technique, and methods of establishment. Rye, oats, wheat, hairy vetch, and crimson clover are all types of cover crops that were reported as being used in cover crop systems. The consensus among focus group participants was that herbicide burn-down was the preferred method for terminating a cover crop. It was on rare occurrence that a small percentage of farmers recalled atypical years that required another approach. In particular, some expressed that during the years of excessive rainfall, they were unable to access their fields, requiring the use of controlled burn to terminate cover crops. This remains a less preferable method since it results in lesser weed control and soil moisture holding capacity, and the lack of frequent frost prohibits frost termination from being reliable. Broadcasting and drilling seeds into the ground were found to be the two dominant methods of establishing cover crops. However, one farmer reported that their crimson clover reseeded itself each year, eliminating the need to replant cover crops annually despite crimson clover commonly being classified as an annual plant.

As observed in Figure 1, the original motivation for planting cover crops was mostly limiting or preventing soil erosion. After a farmer mentioned soil erosion control as their original motivation for planting cover crops, they were asked to clarify whether they were referring to wind erosion or water erosion. Most commonly, when farmers were posed with this question, they would indicate that both wind and water erosion control were motivations for planting cover crops.

When farmers were asked to identify their current motivations for planting cover crops as opposed to original motivations, the reasons they offered were much more varied, as shown in Figure 2. Producers explained that over several years of planting cover crops, they began to reap unintended benefits, such as being able to reduce their number of irrigation applications and reduced weed pressure from the noxious weed palmer amaranth because cover crop residue minimized sunlight reaching the soil. Although soil erosion control remained the most commonly stated reason for currently planting cover crops, increasing soil water holding capacity and reduced need for cultivation were more commonly expressed as current motivations for planting cover crops in cotton and peanut production systems.

In focus groups, nine farmers indicated that by planting a cover crop they were able to simply terminate the crop with herbicide and plant their cotton and peanuts without other extensive preparation such as field cultivation. Moisture retention over the growing season was another benefit of planting cover crops that was mentioned by eight producers. Remaining cover crop biomass and increased organic matter resulting from planting cover crops enabled farmers to irrigate their crops less frequently and increase productivity in dryland acres. Weed suppression was also a commonly stated current motivation for planting cover crops. However, research findings indicate that cover crop use rarely influenced insecticide and fungicide application decisions in cotton and peanut production.

Interestingly, five farmers reported that drought risk management was an important current motivation in their decision to plant cover crops. Farmers explained that in years of limited rainfall, fields without irrigation were more productive when a cover crop had been planted in the previous year because these fields were able to retain large quantities of water that could be used during dry periods. Conversely, during years of excessive rainfall, it was reported that fields planted after a cover crop were less productive than those not previously planted in a cover crop. Therefore, to neutralize farm production risks farmers would plant some of their acres in cover crops to hedge against drought and not plant cover crops on other acres to hedge against a season of excessive rainfall.

After farmers answered questions about their original and current motivations for planting cover crops, they were asked about their individual budget changes observed from planting cover crops. In many instances, at least one budget change was associated with a mentioned current motivation for planting cover crops. As observed in Figures 3 and 4, cover crops were reported to have both positive and negative impacts on farm costs and revenues. The majority of budget changes reported to be associated with cover crop use were related to costs rather than revenues for cotton and peanut production.

Aside from the initial costs of establishing a cover crop, such as the costs of seed and fuel used during cover crop planting, numerous positive and negative cost changes were reported to be associated with cover crop adoption. Most cost changes reported in focus groups were cost reductions. However, some producers did report that their decision to plant cover crops increased their cotton and peanut seeding rate, mandated additional herbicides to terminate cover crops, and required purchasing additional farm equipment. However, several farmers explained that they did not view the cost of a burn-down herbicide application as an additional cost for cover crop. These farmers apply a spring burn-down herbicide, such as glyphosate, even if they do not plant cover crops to eliminate winter weeds.

Focus group participants did identify a few notable revenue changes resulting from cover crop usage, as shown in Figure 4. Reported revenue changes resulting from planting cover crops include occasional yield increases, selling harvestable cover crops, grazing livestock on cover crops, and payments from government programs. Farmers reported conflicting changes about yield resulting from planting cover crops. Five farmers reported that yield for their cash crops increased, while four farmers reported decreased yield. Although both positive and negative yield changes were reported in focus groups, most farmers agreed that cotton and peanut yields were only minimally influenced by a previously planted cover crop. Cost share programs were found to be the most commonly reported revenue change resulting from cover crop use, with nine farmers indicating that they received some additional revenue from either the Conservation Stewardship Program (CSP) or the Environmental Quality Incentives Program (EQIP). Finally, two producers reported that they observed a revenue increase from planting cover crops in the form of selling harvested cover crops and providing grazing for livestock.

The focus group interviews revealed that soil erosion, cultivation, and irrigation applications are some of the production variables most impacted by cover crop adoption. Although the exact cost of erosion is difficult to quantify, erosion prevention was the leading motivation for planting cover crops among farmers. Farmers explained that controlling erosion saved them money for multiple reasons. By preventing soil erosion, farmers eliminate the cost of repairing field washouts and prevent nutrients from being carried out of their fields. Similarly, focus group participants explained the benefits of planting cover crop to be able to plant cash crops without cultivation, which resulted in fuel saving since field cultivation equipment requires large amounts of fuel to operate. Cover crop residue was reported by eight farmers to decrease irrigation requirements, which saved the farm irrigation expenses.

CONCLUSION

Qualitative data collected from focus group interviews provides an insightful view of how cover crop utilization affects farm profitability. There are costs and revenue changes associated with this conservation practice. Focus group participants indicated that controlling soil erosion, reducing annual irrigation requirements, and eliminating field cultivation were among the most notable benefits of cover crop adoption. Similarly, the major expenses related to cover crop adoption were the additional cost of cover crop seed, fuel for planting cover crops, herbicide application, and labor. These findings are valuable information in determining the direction of the effects of cover crops on farm profitability. However, to determine the magnitude of the effects, future research should include quantitative data collection.

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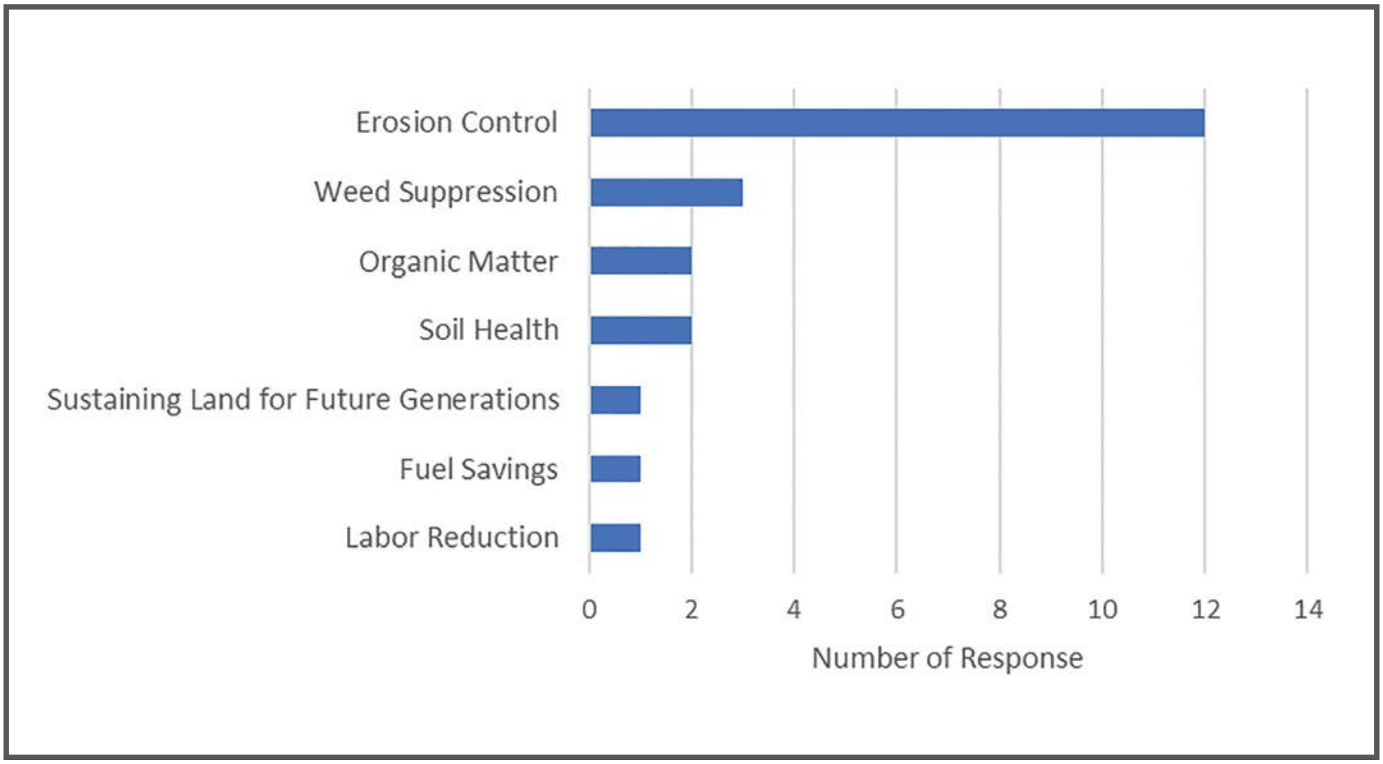

Figure 1. Most Commonly Stated Initial Reasons for Planting Cover Crops in Georgia

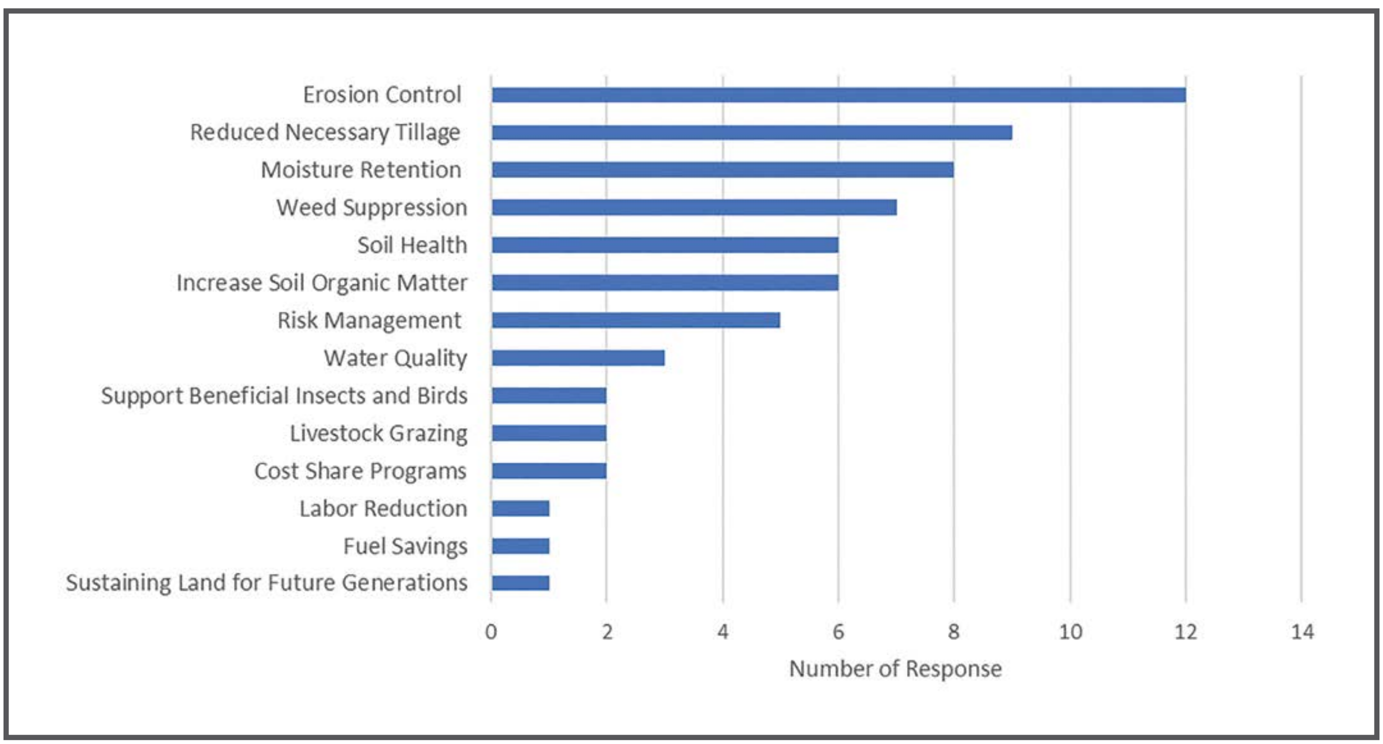

Figure 2. Most Commonly Stated Current Reasons for Planting Cover Crops in Georgia

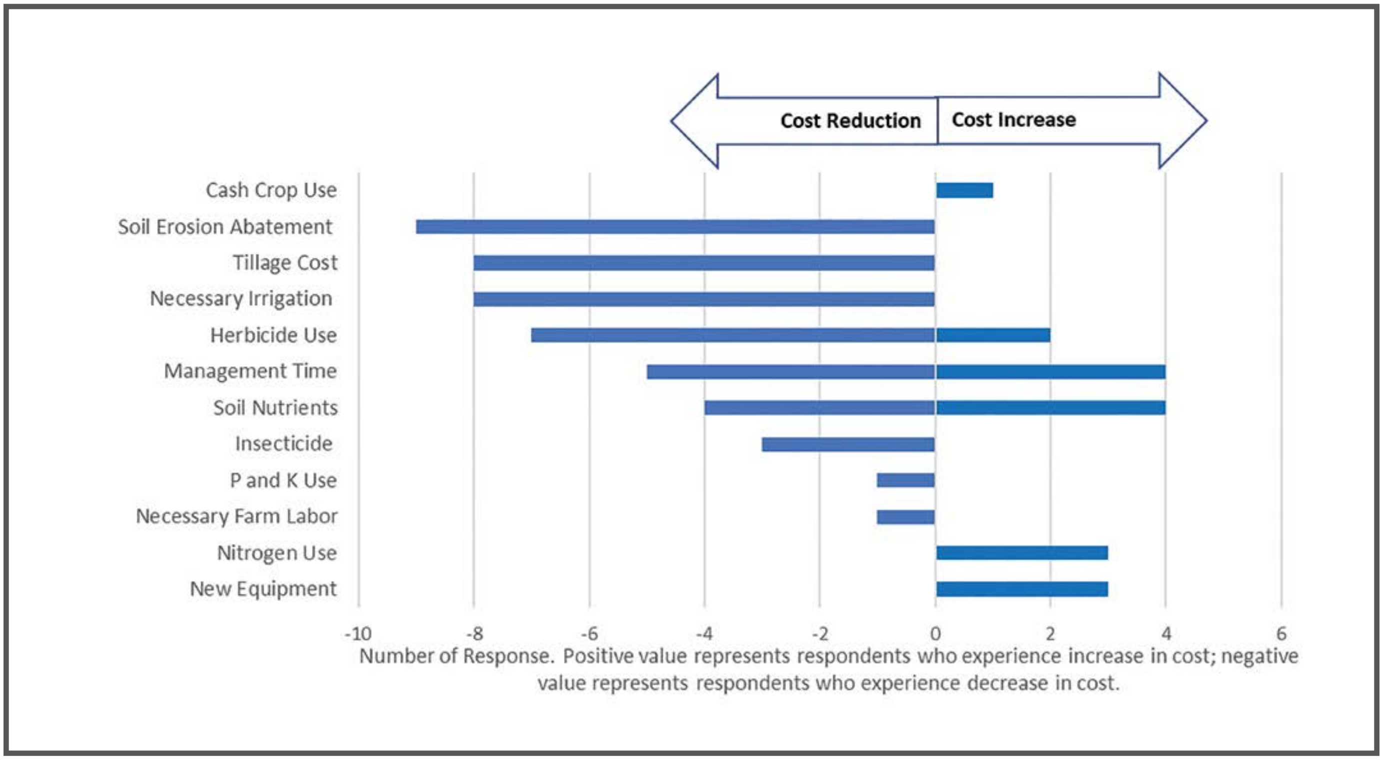

Figure 3. Reported Cost Changes Associated with Cover Crop Use

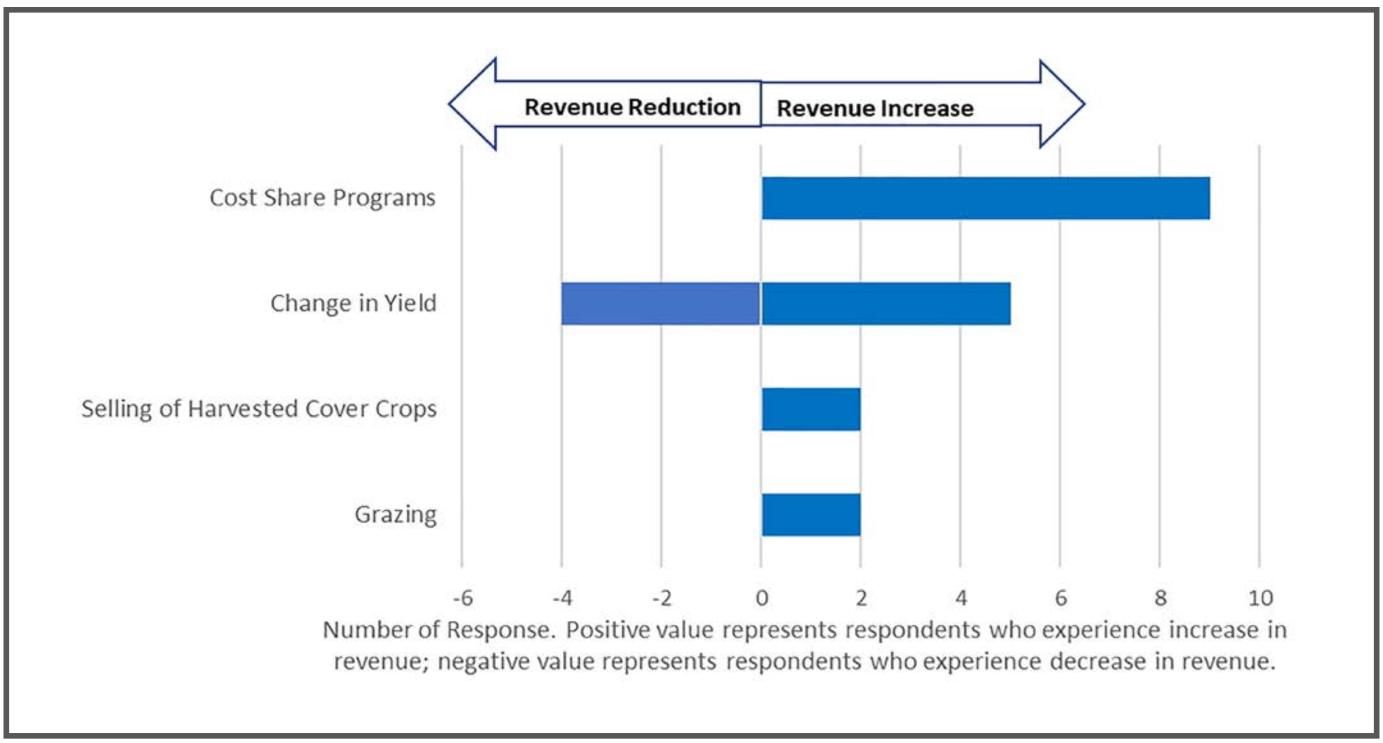

Figure 4. Reported Revenue Changes Associated with Cover Crop Use

Department of Agricultural and Applied Economics
College of Agricultural & Environmental Sciences
UNIVERSITY OF GEORGIA

An Economic Analysis of Cover Crop Utilization in Georgia Cotton and Peanut Production

Goals

Science-based information on the potential return on investment for cover crops in the in Southern Coastal Plain is very limited. The first goal of this project is to develop and promote the use of partial budgets for cover crops in southern cotton and peanut row crop farming. The marginal benefits and the marginal costs of cover crops will be compared against a control scenario of leaving the land fallow during winter to assess the annual net benefit of adopting cover crops.

Timeline

Meetings will be conducted with groups of experienced cover crop farmers each to record farm management practices, associated changes in costs and revenues related to the practice. Based on the information collected through the focus groups, a survey instrument will be made available to validate and expand on the original results. A final report with benchmark partial budgets will be complete in 2019.

Privacy of the data

Data collected through the focus groups and the survey will be de-identified: the names and/or physical addresses of the respondents will not be recorded. Only regional averages (not identifiable data) will be made publicly available in the final report and all other publications stemming from this project.

If you have any questions related to this research project, you can contact Dr. Yangxuan Liu at (229) 386-3512 – Yangxuan.Liu@uga.edu, Ms. Amanda Smith at (229) 386-3512 – a.Smith@uga.edu, Dr. Alejandro Plastina (515) 294-6160 – Plastina@iastate.edu or Guy Hancock at (229) 425-6279 – ghancock@uga.edu.

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Sign me up!

Participation in the Focus Groups is voluntary. I hereby acknowledge my intention to participate in the Focus Groups and survey planned for this study, in exchange, receive a detailed cost-benefit analysis of cover crop for my farm.

Name ______________________________ Signature ___________________ Date ________

Address____

Telephone (____)____________________ Email ____________________________________

Appendix 1. Focus Group Consent Form

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An Economic Analysis of Cover Crop Utilization in Georgia Cotton and Peanut Production

Date and Location

Focus Group Discussion. Moderator: Guy Hancock

Question 1: "Please tell us who you are, where your farm is, what your soil types are, and the year when you first planted cover crops."

Question 2: "Think back to when you did not plant cover crops, what prompted you to plant cover crops the first time?"

Question 3: "What drives you to plant cover crops today?"

Question 4: "Please describe your multi-year rotations that include both cotton and peanuts in most of your acres with cover crops versus the multi-year rotations without cover crops."

Question 5: "Describe the **differences in management practices** for a cotton-peanut or cotton-cotton rotation with cover crops versus a rotation without cover crops."

Question 6: "Compared to the alternative of leaving land fallow during winter, what **new or additional revenue** have cover crops generated for you?"

Question 7: "Compared to the alternative of leaving land fallow during winter, what **costs have you actually eliminated or reduced** in a cotton-peanut or cotton-cotton rotation by using cover crops?"

Question 8: "Compared to the alternative of leaving land fallow during winter, what **new or additional costs** have you actually incurred in a cotton-peanut or cotton-cotton rotation due to cover crops?"

Question 9: "Compared to the alternative of leaving land fallow during winter, what **revenue have you actually lost or seen decline** in a cotton-peanut or cotton-cotton rotation due to cover crops?"

Question 10: "How many acres do you farm and how many of those acres are currently planted in a cover crop?"

Appendix 2. Focus Group Questions

Comparing Net Return to Land and Risk for Alternative Leasing Arrangements

By Michael Langemeier and Yangxuan Liu

Michael Langemeier is a Professor in the Department of Agricultural Economics at Purdue University. Yangxuan Liu is an Assistant Professor in the Department of Agricultural and Applied Economics at the University of Georgia.

Abstract

This paper examined the net return to land and risk for crop share, fixed cash rent, and flexible cash lease arrangements. Specifically, certainty equivalent analysis was used to compare the risk-adjusted net return to land for each leasing arrangement, and a downside risk model was used to determine the optimal mix of leasing arrangements from a landlord perspective. The preferred leasing arrangement for a risk neutral landlord was the flexible cash lease arrangement. Landlords that were slightly, moderately, and strongly risk averse preferred the fixed cash rent arrangement. Results of the downside risk model emphasized the importance of using a combination of the leasing arrangements for landlords with multiple land tracts. A relatively large reduction in downside risk with little change in net return to land could be achieved by utilizing a combination of the fixed cash rent and flexible cash lease arrangements, rather than just utilizing the flexible cash leasing arrangement, which had the highest expected net return.

INTRODUCTION

Obtaining control of land through leasing has a long history in the United States. Leases on agricultural land are strongly influenced by local custom and tradition. However, in most areas, landowners and operators can choose from several types of lease arrangements. These lease arrangements include crop share arrangements, fixed cash rent arrangements, and flexible cash lease arrangements. With crop share arrangements, crop production and often government payments and crop insurance indemnity payments are shared between the landowner and the operator. These arrangements also involve the sharing of at least a portion of crop expenses. Fixed cash rent arrangements, as the name implies, provide landowners with a fixed payment per year. Flexible cash lease arrangements provide a base cash rent plus a bonus, which typically represents a share of gross revenue in excess of a certain base value.

Several previous studies have compared the net return and risk of alternative leasing arrangements. Barry, Escalante, and Moss (2002) examined the rental spread between cash and share leases in Illinois from 1995–1998 and determined how these spreads were related to risk and other farm characteristics. Share leases included government payments and crop insurance proceeds. In north and central Illinois for high productivity soil, share rents were $3.39 per acre higher than cash rents. For southern Illinois, share rents were $2.63 lower than cash rents. The rental spread tended to be lower when cash rents were relatively high on more productive soils and for farmers with relatively higher net worth.

Davis (2004) used a simulation model to examine net returns for landowners and tenants under cash, share, and flexible leases in South Carolina. Flexible leases that accounted for crop price variability, yield variability, and crop price and yield variability were included in the analysis. Landowners received the largest rent from a crop share lease, and the fixed cash lease was ranked as the least preferred lease arrangement.

A simulation model was also used by Edwards and Hart (2013) to examine the financial risk borne by tenants and landlords under 10 different types of flexible cash leases. Flexible lease types examined included those based on yield variability; crop price variability; yield and crop price variability; and yield, crop price, and cost variability. They referred to a flexible cash lease that computed rent using a base cash rent plus a fixed percent times actual gross revenue in excess of the actual cost of production as a "profit share" lease. This lease type is similar to the flexible cash lease examined in this study. Of the flexible lease arrangements examined, the profit share lease was found to shift the most risk from the tenant to the landowner and provided the tenant with the lowest probability of suffering a loss in a given year.

Paulson (2012) noted that the returns for a flexible cash lease are a hybrid of the returns realized under fixed cash and share rent leases. The flexible cash leases examined in the analysis included a base cash rent and a share of realized crop revenue. Schnitkey (2015) proposed examining a similar flexible cash lease as an alternative to reducing fixed cash rents. The idea behind this notion is straightforward. A landowner may be willing to reduce their base cash rent if there is a nontrivial chance that they could share in higher crop revenues if they occur. The flexible cash leases discussed by Paulson (2012) and Schnitkey (2015) are similar to the flexible cash lease examined in this study.

The objective of this paper is to examine the net return and risk of crop share, fixed cash rent, and flexible cash leasing arrangements. Comparisons are made from a landlord perspective using data for west central Indiana. The west central region of Indiana contains some of the best soils in Indiana and has trend corn yields that are slightly above the U.S. average. In addition to determining the risk-adjusted net return to land for each leasing arrangement, tradeoffs are developed so that alternative leases can be compared from both a net return to land and risk perspective.

RISK ANALYSIS

Landowners with different degrees of risk aversion may prefer different leasing agreements. Recognizing this, we incorporated landowners' risk attitudes into the decision-making framework. Thus, in addition to comparing the average, standard deviation, and coefficient of variation (standard deviation divided by the average) between leasing arrangements, the risks associated with net return to land for the leasing arrangements are compared. The certainty equivalent of net return represents a risk-adjusted return and is computed using expected utility theory, which requires a specific utility function and specific levels of risk aversion. As risk aversion increases, the certainty equivalent of net return decreases. In essence, higher risk aversion increases the potential cost of risk, resulting in a lower certainty equivalent or risk-adjusted net return. For each level of risk aversion, a leasing arrangement with a higher certainty equivalent is preferred to a leasing arrangement with a lower certainty equivalent.

To calculate the certainty equivalent requires information pertaining to the utility function and the risk aversion coefficients. The power utility function was used to compute certainty equivalents in this study. This utility function is often referred to as the constant relative risk aversion utility function and is widely used for modeling risk aversion in production agriculture (e.g., Liu et al., 2018). In addition to constant relative risk aversion, this utility function exhibits decreasing absolute risk aversion as wealth increases. Relative risk aversion levels of 0, 1, 3, and 5 were used in this study. A relative risk aversion level of 0 is applicable to a risk neutral decision-maker. Risk aversion levels of 1, 3, and 5 represent slightly, moderately, and strongly risk averse preferences (Hardaker et al., 2015). Using a range of risk aversion coefficients captures the wide range of risk preferences exhibited by landowners.

Sensitivity analyses involving the crop share percentage and flexible cash lease parameters were also conducted using slightly risk averse preferences. Specifically, for the crop share leasing arrangement, the crop share percentage that would yield the same or a higher certainty equivalent of net return as the fixed cash rent arrangement was computed. Similarly, the bonus split or base cash rent needed to make the certainty equivalent of net returns to land for the flexible cash lease arrangement equal to or higher than that of the fixed cash rent lease arrangement was computed.

Expected net return and risk for combinations of the lease arrangements were examined with a downside risk model. The Target MOTAD model maximizes expected income subject to a constraint or limit on the total negative deviations measured from a fixed target or target income (Tauer, 1983; Watts, Held, and Helmers, 1984). The Target MOTAD model focuses on the downside risk that occurs when the net return to land falls below a target level. As with other portfolio models, tradeoffs between risk, as measured by the total negative deviations below a target income, and expected income are examined. The solution of the model that identifies the maximum expected income also has the highest level of total negative deviations below the target income. In other words, this is the profit maximizing solution. As the total negative deviations below the target income become more constrained, risk and expected income decline. A target income or net return to land of $200 per acre is used for the analysis in this paper. This target income is similar to the lowest average net return to land for the leasing arrangements examined in this paper. This target income can be thought of as the long-term average net return to land.

FARM SETTING

Net returns to land from 1996–2018 from a landowner perspective were computed for a case farm in west central Indiana that utilized a corn/soybean rotation. Lease arrangements examined included a crop share lease, a fixed cash rent lease, and a flexible cash lease.

With the crop share lease, the landlord received 50% of all revenue (crop revenue, government payments, and crop insurance indemnity payments). In addition to providing the land, the landowner paid 50% of seed, fertilizer, and chemical (herbicides, insecticides, and fungicides) expenses, as well as 50% of crop insurance premiums. The case farm participated in crop insurance and government programs.

Fixed cash rents were obtained from the annual Purdue Farmland Value Survey (e.g., Dobbins, 2019). Specifically, cash rents for average productivity land in west central Indiana were used. The flexible cash lease arrangement used a base cash rent that was 90% of fixed cash rent. In addition to the base case rent, the landowner received a bonus of 50% of the profit if the revenue exceeded non-land cost plus base cash rent. The profit is calculated as the gross revenue above non-land cost plus base cash rent. Gross revenue included crop revenue, government payments, and crop insurance indemnity payments. All cash and opportunity costs, except those for land, were included in the computation of non-land cost.

Table 1 presents the annual net return to land per acre for the fixed cash rent, flexible cash, and crop share leasing arrangements. All net returns in Table 1 were adjusted for inflation using the implicit price deflator for personal consumption expenditures and are expressed in real 2018 dollars. Figure 1 also conveys annual net return information for the three lease arrangements. The flexible cash lease arrangement had a higher net return to land than the fixed cash rent lease arrangement in 1996, 2007, 2008, and from 2010–2012. Bonuses were paid in 1996, 1997, 2000, 2002, 2006–2013, and 2018. The largest bonuses were paid in 2007–2008 and 2010–2012. During the period often referred to as the ethanol boom (i.e., 2007–2013), the average bonus per acre was approximately $58. The crop share lease arrangement had a higher net return to land than the fixed cash rent lease arrangement in 1996 and from 2007–2012. Essentially, the flexible cash lease arrangement exhibits some of the upside potential of the crop share lease arrangement, while protecting net returns on the downside. Although net return to land for the flexible cash lease arrangement was not as high as that for the crop share lease arrangement during several of the ethanol boom years, it did a good job of mitigating the drop in net return to land from 2003–2005 and from 2013–2017.

RESULTS

The minimum, maximum, average, standard deviation, and coefficient of variation of net return to land per acre for each leasing arrangement are presented in Table 2. The flexible cash lease arrangement had a higher average net return over the 1996–2018 period than the other two lease arrangements. However, the standard deviation of net returns and the coefficient of variation, a measure of relative risk, were relatively lower for the fixed cash rent lease arrangement.

Table 3 summarizes the certainty equivalent of net return to land for each leasing arrangement using relative risk aversion levels of 0, 1, 3, and 5. Risk neutral landlords (i.e., $r = 0$) would prefer the flexible cash lease arrangement. Slightly risk averse, moderately risk averse, and strongly risk averse landlords (i.e., $r = 1$, $r = 3$, and $r = 5$) would prefer the fixed cash rent arrangement. Note that the difference in the certainty equivalent between the fixed cash and flexible cash lease arrangements increases as decision-makers become more risk averse. This result suggests that the flexible cash lease arrangement is relatively risky compared to the fixed cash rent arrangement, resulting in a relatively faster increase in the cost of risk for the flexible cash lease.

Sensitivity analysis was conducted to determine the flexible cash lease and crop share parameters needed for these alternatives to have the same or a higher certainty equivalent of net return to land as that for a landlord who utilizes the fixed cash rent arrangement and is slightly risk averse (i.e., $r = 1$). For the flexible cash lease arrangement to have the same or higher certainty equivalent, either the bonus needs to increase to 54% with the 90% base rent or the base rent needs to increase to 91% with the bonus staying at 50%. For the crop share arrangement, the share of revenue and expenses would need to increase to 55% for the certainty equivalent for this arrangement to be the same or higher than the certainty equivalent for the fixed cash rent arrangement. This 55% crop share is considerably higher than the traditional crop share (i.e., 50%) utilized in the study region.

Using the Target MOTAD model, the tradeoffs between risk—as measured by the total negative deviations below the target income of $200 per acre—and expected income or net return are illustrated in Table 4 for scenarios or levels of risk. The expected net return to land, the total amount of negative deviations below the target income or net return, and the optimal mix of leasing arrangements is presented for each scenario. The total negative deviations represent the sum of the negative deviations over the 23-year period.

The scenario that maximizes expected net return (i.e., scenario 1) had the highest risk level and utilized the flexible cash leasing arrangement. Scenario 7 had the lowest risk level, the lowest expected income, and utilized the fixed cash rent leasing arrangement. The other scenarios utilized a combination of the fixed cash rent and flexible cash leasing arrangements. The crop share leasing arrangement did not appear in any of the scenarios in Table 4. Given its relatively low average net return to land and relatively high standard deviation of net returns to land, it was not surprising to find that this leasing arrangement was not part of the optimal mix for any of the scenarios. To provide some information as to how risky the crop share arrangement is, the Target MOTAD model was solved for the situation in which the crop share arrangement was utilized. For this scenario, expected net return was $200.57 per acre and total negative deviations below the target income or net return were $548.12 or an average of $23.43 per year. In contrast, the average deviations per year for the fixed cash rent and flexible cash leases were $11.65 and $16.83, respectively. Obviously, the deviation levels for the crop share leasing arrangement are substantially higher than those presented in Table 4.

It is evident from the results in Table 4 that deviations below the target income or net return can be reduced rather substantially with small reductions in expected net return to land. For example, going from scenario 1 to scenario 3 reduces expected net return to land by only $0.41 per acre but reduces negative deviations below target income by 9.6%. Similarly, going from scenario 1 to scenario 5 reduces expected net return to land by $0.98 per acre and reduces negative deviations below the target income by 22.5%. Scenario 7 has an expected net return to land that is $1.52 lower than the net return to land for scenario 1 and $0.54 lower than the net return to land for scenario 5. Negative deviations below the target income for scenario 7 are 30.8% and 10.7% lower than those for scenarios 1 and 5, respectively.

Figure 2 presents the annual net return to land for the fixed cash rent arrangement (i.e., scenario 7) and the combination of the fixed cash rent and flexible cash lease arrangements for scenario 5 (labeled as CR/FR Combination in Figure 2), along with the target income. Interestingly, scenario 5 has higher negative deviations than scenario 7 from 1997–2006, in 2009, and from 2013–2018. However, its net return to land is substantially higher in 2007, 2008, and from 2010–2012.

SUMMARY AND CONCLUSIONS

This article compared the net return to land for crop share, fixed cash rent, and flexible cash leases. The net returns to land from a landowner perspective were similar for the fixed cash and flexible cash leases. The crop share lease had a relatively lower average net return to land. The flexible cash lease mimicked the ups and downs of the crop share lease. However, the upward and downward spikes for the flexible cash lease were less pronounced than those for the crop share lease. Choosing among the leases depends on a landowner's desire to capture improvements in crop share revenue and ability to withstand downside risk. The crop share and flexible cash leases allow landowners to more fully capture annual improvements in crop revenue but also increase the probability of significant downward movements in annual net returns.

The flexible cash lease had the highest average net return to land; thus, this leasing arrangement would be preferred by a risk neutral landowner. Slightly risk averse, moderately risk averse, and strongly risk averse landowners preferred the fixed cash rent leasing arrangement. Landlords do not necessarily have to use the same leasing arrangement for all of their land tracts. To accommodate this fact, a portfolio model that focuses on downside risk was utilized. Results show that choosing a combination of leasing arrangements can allow landowners to better capture annual improvements in crop revenue but also reduce the probability of downward movements in annual net returns. Downside risk for the flexible cash leasing arrangement was higher than it was for a combination of the fixed cash rent and flexible cash leasing arrangements. The decrease in net return to land resulting from adding the fixed cash rent arrangement to the flexible cash lease rent arrangement was negligible. By utilizing a combination of the fixed cash rent and flexible cash lease arrangements, rather than just utilizing the flexible cash lease arrangement, landowners could achieve a large reduction in downside risk with little change in net return to land.

This paper utilized historical net returns to examine leasing arrangements. Since 1996, there have been periods in which the net return to land was relatively stable regardless of the leasing arrangement, as well as a boom and bust period (i.e., 2007–2018). Choice of leasing arrangements also depends on a landowner's expectations regarding commodity prices. Landowners who are expecting stable commodity prices and net returns may be better off using a fixed cash rent leasing arrangement rather than using a portfolio approach. Landowners who are concerned about what may occur if we have another boom and bust period would find the portfolio approach or an arrangement other than the fixed cash rent leasing arrangement more attractive.

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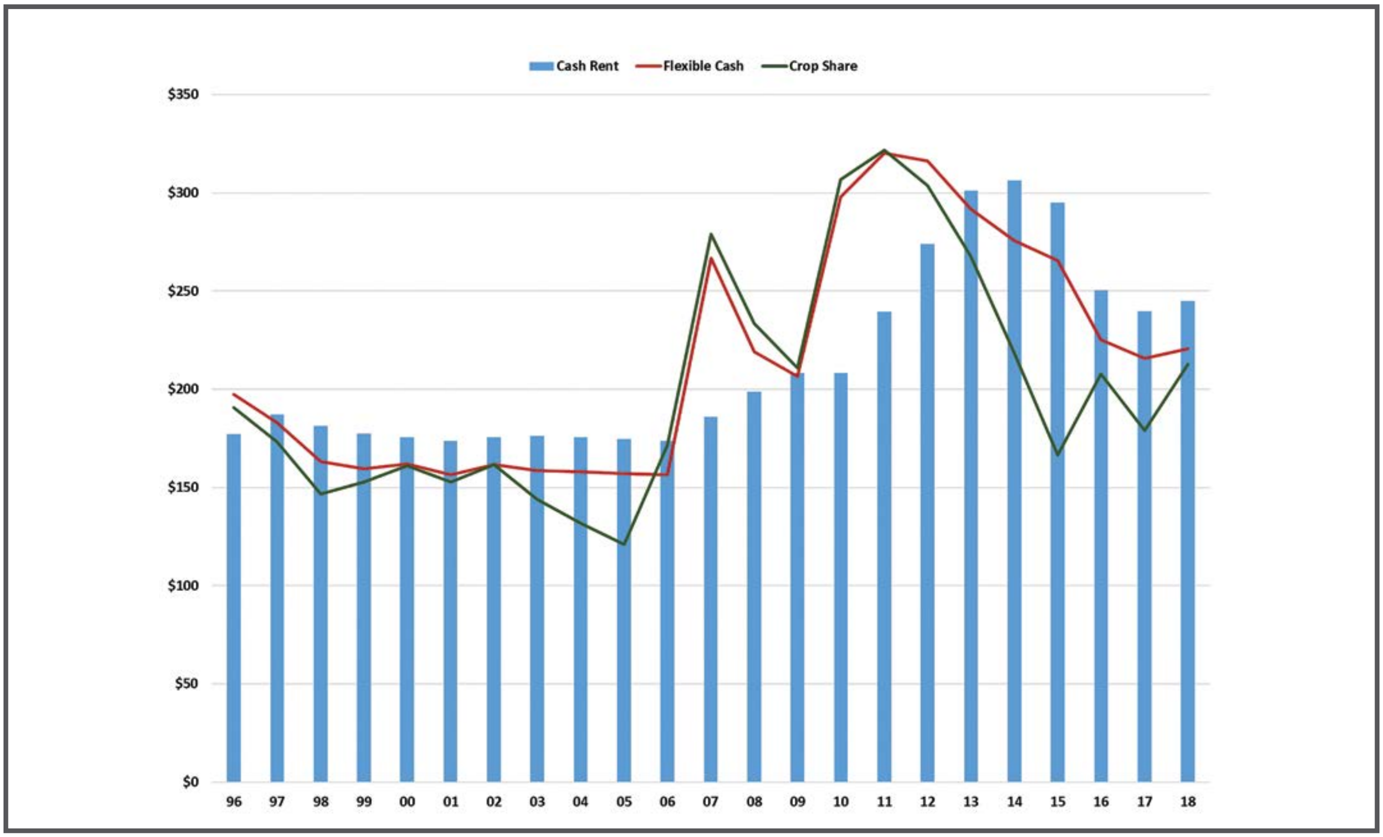

Figure 1. Real Net Return to Land for Alternative Leasing Arrangements (Source: Table 1)

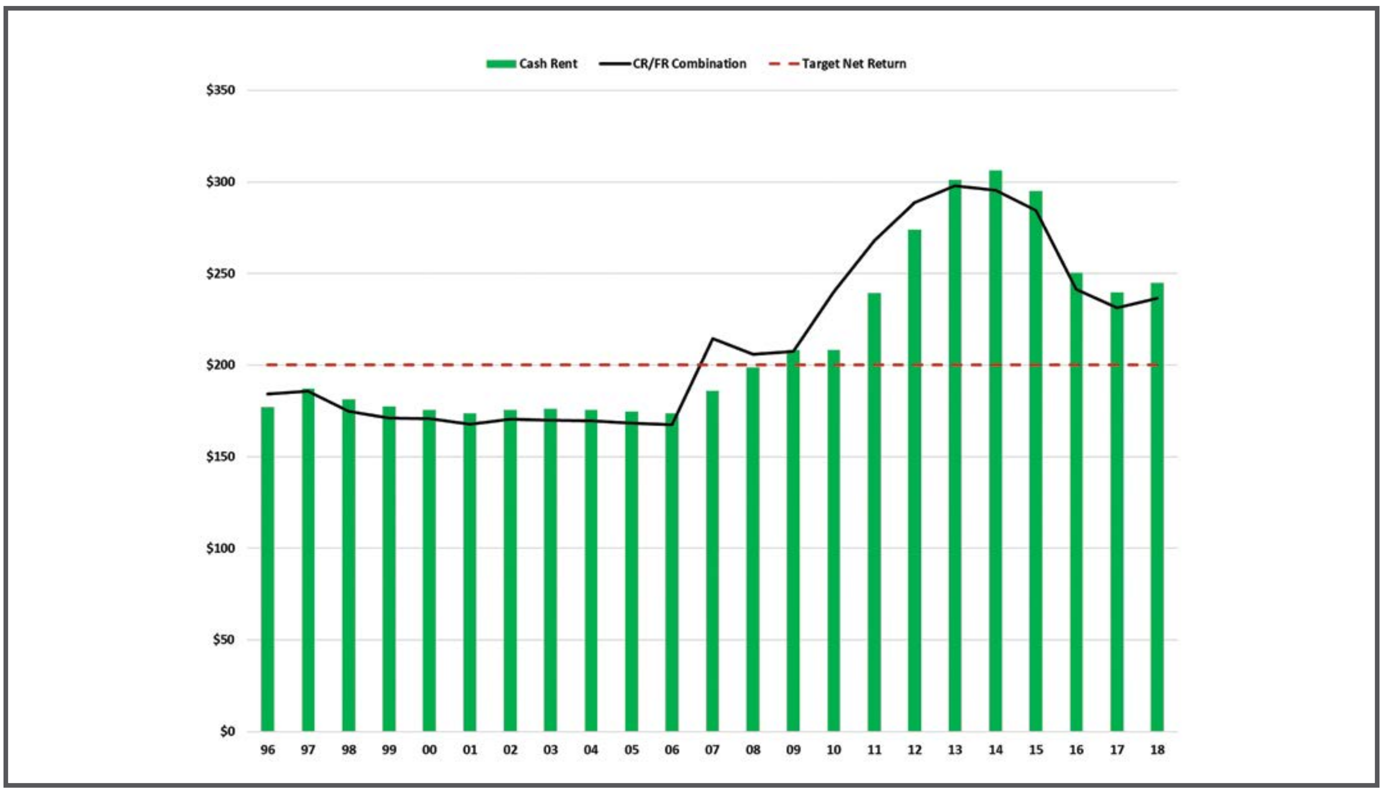

Figure 2. Comparison of Fixed Cash Rent and Combination of Fixed Cash Rent and Flexible Cash Lease Arrangements (Source: Target MOTAD results). Note: CR/FR Combination represents a combination of the fixed cash rent and flexible cash lease arrangements (i.e., scenario 5 in Table 4.)

Table 1. Real Net Return to Land per Acre for Cash Rent, Flexible Cash, and Crop Share Leasing Arrangements, West Central Indiana ($ per Acre)					
		Flexible Cash			
Year	Fixed Cash Rent	Base Rent	Bonus	Total	Crop Share
1996	177.07	159.37	37.88	197.25	190.63
1997	187.10	168.39	14.76	183.14	173.12
1998	181.30	163.17	0.00	163.17	146.53
1999	177.22	159.50	0.00	159.50	152.67
2000	175.69	158.12	3.69	161.82	161.09
2001	173.74	156.36	0.00	156.36	152.85
2002	175.50	157.95	3.72	161.67	161.62
2003	176.10	158.49	0.00	158.49	143.83
2004	175.66	158.09	0.00	158.09	131.73
2005	174.54	157.09	0.00	157.09	120.99
2006	173.56	156.20	0.23	156.43	171.34
2007	185.83	167.25	99.48	266.73	278.84
2008	198.81	178.93	40.09	219.02	233.32
2009	208.19	187.37	19.10	206.47	210.80
2010	208.08	187.27	110.60	297.88	306.86
2011	239.33	215.40	104.63	320.03	321.75
2012	273.82	246.44	69.80	316.24	303.72
2013	301.15	271.04	20.84	291.87	267.53
2014	306.17	275.55	0.00	275.55	218.07
2015	294.91	265.42	0.00	265.42	166.44
2016	250.24	225.21	0.00	225.21	207.75
2017	239.78	215.80	0.00	215.80	179.04
2018	245.00	220.50	0.10	220.60	212.53

Table 2. Summary Statistics for Real Net Return to Land per Acre for Cash Rent, Flexible Cash, and Crop Share Leasing Arrangements, West Central Indiana ($ per Acre)			
	Fixed Cash Rent	Flexible Cash	Crop Share
Minimum	173.56	156.36	120.99
Maximum	306.17	320.03	321.75
Average	212.99	214.51	200.57
Standard Deviation	45.75	57.44	59.20
Coefficient of Variation	0.215	0.268	0.295

Table 3. Certainty Equivalent of Net Return to Land for Each Leasing Alternative Under Four Relative Risk Average Assumptions ($ per Acre)

Relative Risk Aversion	Fixed Cash Rent	Flexible Cash	Crop Share
r = 0 (risk neutral)	212.99	214.51	200.57
r = 1 (slightly risk averse)	208.73	207.57	192.88
r = 3 (moderately risk averse)	201.61	195.60	179.88
r = 5 (strongly risk averse	196.35	186.80	170.18

Table 4. Expected Net Return to Land and Total Negative Deviations Below Target Income ($ per Acre)

Scenario	Expected Net Return	Negative Deviations	Fixed Cash Rent	Flexible Cash	Crop Share
1	214.51	387.00	0.000	1.000	0.000
2	214.38	375.00	0.089	0.911	0.000
3	214.10	350.00	0.275	0.725	0.000
4	213.81	325.00	0.461	0.539	0.000
5	213.53	300.00	0.647	0.353	0.000
6	213.23	275.00	0.845	0.155	0.000
7	212.99	267.89	1.000	0.000	0.000

Impact of Short-Run Weather Fluctuations on Farmland Sales and Values


By Arisha Ashraf and Ariel Dinar

Arisha Ashraf is a Consultant with the Water Utility Consulting Firm Raftelis. Ariel Dinar is a Distinguished Professor in the School of Public Policy at the University of California, Riverside.

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Abstract

As the frequency and duration of droughts persist in Southern California, we may witness more agricultural land sales among both agricultural producers and non-agricultural users. How is this related to land value? Do the same factors that increase land value also increase the likelihood of land sales? We analyze the extent to which short-run weather shocks associated with California droughts (2007–2009 and 2011–2016) influence the sale and value of agricultural parcels. We employ a population- averaged panel logistic analysis and a Ricardian model across 17 years (2000–2016) of parcel data in Riverside County, California. The history of farming in Riverside County extends to over a century, with many growers holding senior water rights. The western part of the county is experiencing rapid population growth, increasing the pressure for agriculture-to-urban water transfers. Persistent drought would only exacerbate the viability of farming in the region. Although we do not find a significant relationship between the likelihood of selling farmland and precipitation variability, we do find that precipitation variability reduces the value of farmland. We also find that increase in population rate decreases the likelihood of land sales while increasing land value. It would be insightful to determine the extent to which different attributes that contribute to land value also contribute to the likelihood of selling agricultural land. In particular, it would be insightful for appraisal methodologies to incorporate drought persistence into the existing frameworks.

INTRODUCTION

In their seminal work, applying the Ricardian technique to estimate the value of climate in agriculture, Mendelsohn, Nordhaus, and Shaw (1994) introduce the concept of adaptation by farmers in the form of adjusting land use patterns to changes in environmental variables. They show how farmers adjust to worsening climate conditions by changing their cropping patterns (and management practices). At extreme climate conditions, farmers may no longer farm but rather convert land to non-agricultural activities—what Mendelsohn, Nordhaus, and Shaw (1994) coin "retirement home." We extend the notion of "retirement home" and refer to land sale as the transaction that occurs prior to getting out of farming. In countries where there are no markets for agricultural land, farmers just move out from farming as a response to harsh climatic conditions (Maddison, 2007). In the presence of markets for agricultural land, exiting farmers can sell their land to more efficient farmers, so it remains in agricultural production, or it can be sold to non-agricultural uses, such as urban dwelling.

We study the impact of climate on the likelihood of land sale and land value in two complementary analyses.[1] We focus on Riverside County in California for these analyses because it presents a high degree of variation in land use, crop mix, climate, and water district services. Riverside County has a complex relationship among quality farmland (i.e., good soil), senior water rights, high urbanization rate, and high value crop production. In these ways, it represents a microcosm of the future threats to the sustainability of agriculture in California.

The first empirical analysis in this paper is on the extent to which climate impacts the likelihood of agricultural land sales. This is particularly challenging to study because agricultural land is not sold very often. On average, 3% to 5% of agricultural parcels are sold in the United States annually (Gloy et al., 2011). Climate extremes, such as drought, are expected to have a greater influence on the likelihood of a land sale than average climate conditions (Mendelsohn et al., 2007). Indeed, the time horizon for our analysis (2000–2016) includes two major drought events (2007–2009 and 2011–2016) to allow us to capture the shocks of extreme climate events. As we noted, there are two types of land sales: one in which agricultural land is sold to another agricultural producer; and another in which agricultural land is sold to non-agricultural users. While climate extremes potentially influence both types of land sales, we focus (mainly due to the dataset we obtained) on land that remains in agricultural production after it is sold. More studies exist elsewhere on the sale of agricultural land for non-agricultural uses (Hoppe and Korb, 2006; Zollinger and Krannich, 2002; Kimhi and Bollman, 1999). Agriculture-to-agriculture land sales are less understood and documented, warranting further analysis. This analysis is also warranted because there is limited understanding of the extent to which microeconomic variables influence the likelihood of land sales of both types. Previous work on agricultural land sales has focused on macroeconomic variables (Devadoss and Manchu, 2007; Huang et al., 2006; Just and Miranowski, 1993).

In the second empirical analysis, we turn to the Ricardian framework in order to assess the extent to which short-run shocks, such as the droughts experienced in California during 2007–2009 and 2011–2016, influence the value of the farming enterprise. We depart from the basic assumption of the Ricardian model that long-run climate patterns (as represented by 30-year normal) are the sole climatic effect determining farmland value. Long-run climatic averages minimize the contribution of extreme events. However, the recent California droughts were more severe than many experienced over the historical record, with projections for increased frequency and duration of these events (Hartmann et al., 2013). For example, the precipitation level from 2012–2014 was the lowest of any three-year running average on record (Williams et al., 2015). Furthermore, 2012–2014 represents the most severe reduction in soil moisture for California of any three-year period over the past 1,200 years (Griffin and Anchukaitis, 2014). In addition to meteorological evidence, perceptions of the severity of drought events may be more prevalent.

While climate is an important determinant, it is not the only factor affecting likelihood of land sale and land value. Controlling for land quality, access to reliable water supply, and urban growth, we evaluate the impact of short-run temperature and precipitation mean and variability (characteristic of the recent extreme drought conditions in California) on land value and sales. We are cognizant of the extent to which the housing market crash in 2007–2008 may have impacted non-agricultural land values, although some argue that historically low interest rates may have caused farmland values to remain relatively high (Nickerson et al., 2012). This may suggest a dampened or ambiguous effect of the housing crisis on farmland values, allowing us to study climatic and weather impacts. Our dataset of Riverside County reveals a drop in both county-wide agricultural revenue and farmland sales during the period of the housing crisis (Figures 1 and 2).

In the next section, we review literature on the determinants of agricultural land sales and literature that includes estimates of extreme climate effects on the value of agricultural land. Based on the findings from previous work, we establish the empirical specifications of the models we use to estimate likelihood of land sales and the value of agricultural land. We then describe the dataset obtained from Riverside County in California and the variables we constructed for the analyses. This is followed by the presentation of the estimated functions of likelihood of land sale and of value of land and by the interpretations of the results. We conclude the paper by discussing results from both analyses on the extent to which short-run weather fluctuations affect the probability of selling agricultural land, as well as the value of agricultural land. While this paper is ultimately focused on quantifying the impact of short-run weather fluctuations on parcel-level land value, we also explore how the likelihood of this sale may be connected to the same fluctuations in short-run weather. These relationships have not been studied previously, and we present preliminary thoughts on how land sales may be linked to farmland values.

LITERATURE REVIEW

Previous work on land sales and land values does not include impact of climate (e.g., precipitation, temperature). Few works exist on determinants of and perceptions about land sales. Positive expectations about the future viability of farming drive capital investment and potentially reduce land sales. Wheeler, Bjournlund, and Edwards (2012) survey attitudes of farmers in the Murray-Darling Basin in southeastern Australia to having their children take over farming operations following the Millennium drought. They find that farmers who plan to have their children inherit their farm are more likely to have made irrigation efficiency improvements and less likely to have sold any land in the prior five years. Zollinger and Krannich (2002) survey Utah growers to determine the factors influencing their expectation of selling land for non-agricultural uses. They find that increased profitability over the past five years has a significant negative influence on the expectation to sell land, while the perception of increased urbanization exerts a significant positive influence.

Deschenes and Kolstad (2011) study how weather and expectations on weather influence farmland productivity in California across a 20-year period. They assume that such expectations are derived from observing past weather, and thus include a five-year moving average in their time-series model. Although none of their weather variables (five-year averages or annual) are significant, their study provides general intuition on the magnitude of these variables. The magnitude of the expected degree-day variable is larger than the annual average, suggesting that changes in expectation are more costly than annual weather changes.

Another set of works focuses on farmland price determinants, employing variables that measure external effects on land values due to urban demand. Drescher, Henderson, and McNamara (2001) find that farmland prices are affected by agricultural production attributes and by demand factors represented by potential development of agricultural land for higher value non-agricultural activities. County-level population growth and value of agricultural sales were found to affect the land price in rural Minnesota. Plantinga, Lubowski, and Stavins (2002) conducted a national-scale analysis of impact of potential land development on agricultural land prices to decompose agricultural land values into a value associated with land productivity and a value associated with future land development (urban pressure).

Zhang, Irwin, and Ward (2010) use a hedonic model to estimate the marginal parcel value attributes in western Ohio. Their findings are very similar to those in this review and those that were observed in our study. The farmland market is a very thin market compared to the urban land market, and the most important determinants affecting the price of land are the agricultural productivity of the parcel, the proximity of the parcel to urban centers, and availability of transportation modes (level of development of the region).

Nilson and Johansson (2013) explore the role of location determinants on agricultural land prices in Sweden. Their findings suggest that regional variation in land productivity, agricultural support payments, and urbanization affect farmland prices. They find also that urbanization factors have a stronger impact on prices in regions with relatively high land values, where agricultural income support to farmers has a stronger impact on prices in regions with lower value of agricultural land.

Mukherjee and Schwabe (2014) estimate the impact on land value of having access to a water supply portfolio. Among several control variables, they also include proximity of the sold parcel to urban centers and the population density in the region. They control for precipitation (which was found not significant) and degree days (representing temperature) during the growing season.

These works focus on micro-level analyses of likelihood of selling farmland and include, to a lesser extent, climatic impacts. In addition, they focus on agricultural land sales for non-agricultural uses, whereas our study focuses on agriculture-to-agriculture land sales. Only Deschenes and Kolstad (2011) and Mukherjee and Schwabe (2014) focus on short-run fluctuations in weather and the impact on land productivity, which we build upon for the subsequent Ricardian analysis.

This paper contributes to the climate change literature by studying the effect of two consecutive drought periods on land values and land sales. Droughts are projected to increase in frequency and duration in semi-arid regions. It is critical to study how drought influences agricultural land value because recurrent drought may impact land appraisal methods in the near future. Riverside County, which is the focus of this study, represents a microcosm of future threats to the sustainability of California agriculture. Such threats include high urbanization rate, shifting to high value crop production, and revocation of water rights.

ANALYTICAL FRAMEWORK

Our analytical framework for estimating the determinants of the likelihood of selling a farm parcel and its value is based on the findings in the reviewed works we presented in the previous section. We develop two models and derive expectations regarding the effects of the explanatory variables on the dependent variables, the likelihood of selling an agricultural parcel, and the value of an acre of the sold parcel. The models are

$$S = f(\underline{R}, \underline{T}, \underline{P}, \underline{C}, \underline{Y}, \underline{D}) \tag{1}$$

and

$$V = g(\underline{R}, \underline{T}, \underline{P}, \underline{C}, \underline{Y}, \underline{D}) \tag{2}$$

where S is the likelihood that a given parcel of a farmland will be sold during the period analyzed; V is the per acre sale price of the parcel; $\underline{R}$ is a measure of rainfall quantity/variability; $\underline{T}$ is a measure of temperature level/variability; $\underline{P}$ is a measure of population density/growth; $\underline{C}$ is crop productivity of the parcel, measured as fixed effect of the crop grown on the parcel; $\underline{Y}$ is year fixed effect, measuring everything but climate effects; and $\underline{D}$ is fixed effects of the services by the water supply agency to the parcel. All explanatory variables are vectors and are marked by an underscore to represent several definitions we used for each. Based on the findings in previous works, we expect effects as summarized in Table 1 of each of the explanatory variables on the dependent variables.

We cannot determine *a priori* the direction of the impact of $\underline{C}$, $\underline{Y}$, and $\underline{D}$ on S and V because these variables (fixed effects) are set without a continuous range. The individual impact would be assessed for each crop type ($\underline{C}$), year ($\underline{Y}$), and water utility ($\underline{D}$). As for the three continuous variables, we expect that as rainfall rate increases, the likelihood of selling a parcel declines and the value of the parcel increases. As rainfall variability increases, the likelihood of selling increases and the value of the parcel is reduced. The opposite is expected to happen in the case of temperature: The higher the temperature, the higher the likelihood of selling a parcel but the lower the value of the parcel. As the variability of temperature increases, the likelihood of selling the parcel increases and the value of the parcel decreases. With population in the neighboring urban center increasing, the likelihood of selling a parcel increases and its value increases as well. The same trends exist for the population growth rate.

EMPIRICAL SPECIFICATIONS

We begin with an exploratory analysis of land sales, analyzing the extent to which land sales are impacted by short-run fluctuations in weather. Our dataset represents parcels that have remained in agricultural production across a 17-year period (2000–2016), with access to irrigation water from four major water districts (Coachella Valley Water District, Eastern Municipal Water District, Palo Verde Irrigation District, and Western Municipal Water District). This is followed by an analysis of the impact of these short-run fluctuations on land values using the same dataset. This ensures that parcels in our dataset are being purchased for agricultural use rather than converted to other uses. Our purpose here is to study farmland value, rather than capture the value of alternative land uses.

Land Sales Analysis

Studying the likelihood of U.S. farmland sales is complicated by the fact that very few such sales take place in a given year relative to the total number of agricultural parcels. Approximately 3% to 5% of agricultural parcels are sold in the United States in a given year (Gloy et al., 2011). On average, 6% of parcels in our panel dataset were sold annually from 2000–2016. We explored the extent to which land sales are influenced by extremes in temperature and precipitation as measured by coefficient of variation of five-year or 10-year expectation periods. The purpose of including measures of averages and variation of temperature and precipitation across five-year and 10-year intervals was to gauge how short-term weather fluctuations may affect land value or the decision to sell land. We use the population-averaged panel model where the likelihood of sale is estimated as a function of climatic variables and population variables (linear and quadratic) in the neighborhood of the parcel, and of several control variables of the crops grown on the parcel and the water district serving the parcel.

The population-averaged panel model is represented as

$$log\frac{q}{1-q} = \alpha_0 + \alpha_1 ppt\_mean_{t-k} + \alpha_2 ppt\_cv_{t-k} + \alpha_3 tmax\_cv_{t-k} + \alpha_4 pop\_rate_{t-k} + \alpha_5 sq\_pop\_rate_{t-k} + \alpha_6 use\_citrus + \alpha_7 use\_irrigated + \alpha_8 use\_vineyard + \alpha_9 use\_date + \alpha_{10} district\_EMWD + \alpha_{11} district\_PVID + \alpha_{12} district\_WMWD + \alpha_{13} year + u_t \tag{3}$$

where *q* is the probability of a land sale. Variables' descriptive statistics and definitions are presented in Table 2. The subscript (t-k) is added to time lagged variables, where t = current year and k represents the number of lagged years (five or 10) used for climatic and population variables.

Ricardian Analysis

In addition to land sales, we study the impact of short-run fluctuations in weather on farmland value using the Ricardian framework. The empirical equation is represented as

$$\log(\text{sale\_acre\_2014}) = \sigma_0 + \sigma_1 ppt\_mean_{t-k} + \sigma_2 ppt\_cv_{t-k} + \sigma_3 tmax\_cv_{t-k} + \sigma_4 pop\_rate_{t-k} + \sigma_5 sq\_pop\_rate_{t-k} + \sigma_6 use\_citrus + \sigma_7 use\_irrigated + \sigma_8 use\_vineyard + \sigma_9 use\_date + \sigma_{10} district\_EMWD + \sigma_{11} district\_PVID + \sigma_{12} district\_WMWD + \sigma_{13} year + u_t \quad (4)$$

Variable descriptive statistics and definitions are presented in Table 2.

DATASET AND VARIABLE CONSTRUCTION/TRANSFORMATION

Dataset

The annual parcel data for 2000–2016 (Assessor Parcel Number, Crop Zone, Sale Year, Sale Value) is taken from the Riverside County Assessor and ParcelQuest. There are 985 recorded parcel sales that include land value within the four major water districts in this analysis. This translates into 16,745 observations (985 × 17) for the land sales model. ParcelQuest includes a greater number of observations of sales than of value associated with these sales. However, we chose to use observations in the dataset, which have both sales and value of sales, in order to make the two analyses in this paper more comparable even if this meant fewer observations in the land sales analysis.

Variable Construction/Transformation

Climate variables are central to our analysis and are represented as

$$E(x_{i,t}) = \frac{1}{k}\sum_{j=t-k}^{t-1} x_{i,j} \quad (5)$$

$$CV(x_{i,t}) = \frac{k}{(k-1)^{1/2}} \frac{\left(\sum_{j=t-k}^{t-1}(E(x_{i,t})-x_{i,j})^2\right)}{\sum_{j=t-k}^{t-1} x_{i,j}} \quad (6)$$

where E is the mean and CV is the coefficient of variation (representing variation in the measured variable over time). $x_{i,t}$ represents either the annual precipitation or the maximum temperature. Year of sale is t, and k is the years lag depending on whether a five-year or 10-year lag is represented. The five-year and 10-year lag values for precipitation and temperature were calculated using the annual average for daily maximum temperature and total annual precipitation (mm) from the PRISM Climate Group, based out of Oregon State University. The PRISM Group develops high-resolution spatial climate datasets from weather station networks nationally, from 1895 to present (http://www.prism.oregonstate.edu).

We do not include temperature mean values in the regression because of the high correlation with precipitation mean values in Riverside County.[2] Even though temperature is an important variable when studying drought, Williams et al. (2015) suggest that precipitation is the primary driver of drought.[3] Furthermore, our descriptive statistics indicate that there is more variance between the precipitation normal and five-year and 10-year mean precipitation values than the analogous maximum temperature normal and maximum temperature five-year and 10-year means.

Annual population growth rate, $\gamma_{i,1}$, for the i^{th} parcel, represents the slope of the population growth line through the five-year or 10-year period prior to the year of sale as

$$pop_i = \gamma_{i,0} + \gamma_{i,1} year \quad (7)$$

where pop_i is the population in the urban neighborhood of the parcel and $year$ is the given year of this population value. The slope is taken at five or 10 years prior to the year of sale. For example, if the year of sale is 2000, then the five-year population rate is calculated using annual population data for 1995–1999.

For the land-use fixed effect, we set the avocado crop as the baseline because it is the most sensitive crop to water scarcity. For the water supply agency fixed effect, we set the Coachella Valley Water District (CVWD) as the baseline because it serves the most water scarce region. And for the year fixed effect, we set the year 2008 as the baseline because it marks the height of the first drought period (2007–2009) in our sample.

DISCUSSION OF RESULTS

We tested the impact of five-year and 10-year lags of weather on both the likelihood of sale and the value of farmland sold. Table 3 presents logit population-averaged panel land sales analysis. Table 4 presents the results of the log-linear parcel-level Ricardian analysis. We focused on the precipitation mean, since this has the greater contribution to drought relative to temperature (Williams et al., 2015). The high degree of negative correlation (–0.97) between precipitation and maximum temperature mean values in Riverside County would introduce multicollinearity if both were included in our analyses. In addition to including the mean precipitation values, we tested the impact of short-run (five-year or 10-year) temperature and precipitation variability on likelihood of farmland sales and on farmland sale value.

None of the climate variables studied impacted the likelihood of selling farmland in Riverside County from 2000–2016. The five-year, 10-year, and 30-year (normal) mean precipitation value also did not impact farmland value. This finding is similar to the results in Deschenes and Kolstad (2011). However, short-run precipitation variability has a significant influence on farmland value. A unit increase in the five-year precipitation coefficient of variation reduces the value of farmland by 56% per acre.

Population rate exhibited a significant relationship with both likelihood of land sales and land sale value. For example, a unit increase in the five-year population rate decreases the likelihood of selling farmland by 32% and increases farmland value by 85%. The exact impact varies across model specifications but remains significant. Furthermore, population rate exhibits a U-shaped relationship with likelihood of land sales and a hill-shaped relationship with land value. The U-shaped pattern is explained by the relationship found between urbanization and land value dynamics. Urbanization naturally follows from population increase, and urbanization tends to increase the value of farmland (Platinga, Lubowski, and Stavins, 2002). This may provide incentives to growers to hold on to their land, rather than selling it, if they expect an urban expansion in the region. However, the marginal productivity of farmland continues to decline with increasing urban encroachment (square of population rate)—and this makes selling farmland more attractive.

Citrus and vineyard parcels are less likely to be sold than avocado parcels, while all other land uses (citrus, general irrigated, vineyard, and dates) tend to be more valuable per acre than avocado. The significance of citrus and vineyards tends to vary across model specifications, although that of general irrigated agriculture and of dates remains robust across these specifications.

At the water district level, the results suggest that more valuable farmland is more likely to be sold. Coachella Valley Water District has the most valuable farmland compared to the other three districts. This suggests that, controlling for other factors, the characteristics of a given water district may add significant value and may be sold to achieve a positive return rather than minimize a loss.

CONCLUSION

Based on our two analyses, we suggest that the relationship between likelihood of farmland sales and sold farmland value is attribute-specific. That is, factors that influence the likelihood of land sale (e.g., land use) may not increase land value, as we had originally hypothesized. Our results suggest that short-run fluctuations in precipitation reduce the value of farmland. This suggests that the droughts experienced during this period may have influenced expectations on the future viability of farming in Riverside County.

Water district influences likelihood of land sales and land value in the same direction. In particular, Coachella Valley Water District has higher sales and value relative to Palo Verde Irrigation District, the other district in Riverside County holding senior water rights. This suggests that expectations on the viability of farming in Coachella Valley Water District are higher even relative to Palo Verde Irrigation District. Other attributes, such as land use, influence farmland sales likelihood and land value in opposite directions. For example, avocado land sales relative to other land uses (citrus and vineyard) increased during this period, whereas land value for avocado declined relative to these other uses. This suggests that avocado orchards may have been sold in Riverside County during the study period due to declining value both relative to other agricultural uses and due to precipitation variability associated with the drought. It is well known that avocado is highly sensitive to water scarcity (Bender et al., 2012).

The relationship between land sale and value is, as suggested earlier, attribute-specific. Higher (lower) land value does not necessarily result in a higher (lower) likelihood of land sale. In addition, our results do not reveal a direct relationship between precipitation extremes (mean or variability) and likelihood of land sale. As previously stated, our results from both models provide indirect evidence that increasing likelihood of sale of avocado parcels may be related to declining land value. In addition, declining land value is, on average, related to increasing precipitation variability. Studying the extent to which selling avocado parcels may represent an adaptation to extreme weather (or climate) is an important area of future research. Avocados are among the most valuable crops with respect to gross revenue per acre. However, as the frequency and duration of drought persists in southern California, we may witness more avocado land being sold not only to other agricultural producers but also to non-agricultural users. The ASFMRA California Chapter has a wealth of data on farm sales and value (http://www.calasfmra.com/trends.php) that could be used to analyze the effects of variations in rainfall and temperature across five years, 10 years, or another interval of years. These variables could be incorporated within the appraisal process based on significant findings.

FOOTNOTES

[1] We decided to include an analysis of the likelihood of land sales based on this data and due to the fact that little has been published on this in previous work. We also decided to keep the analyses separate because nesting one model within another would complicate the interpretation of the results.

[2] For example, the correlation between the maximum temperature normal and precipitation normal is −0.97.

[3] Williams et al. (2015) found that anthropogenic warming contributed between 8% and 27% of the drought anomaly from 2012–2014.

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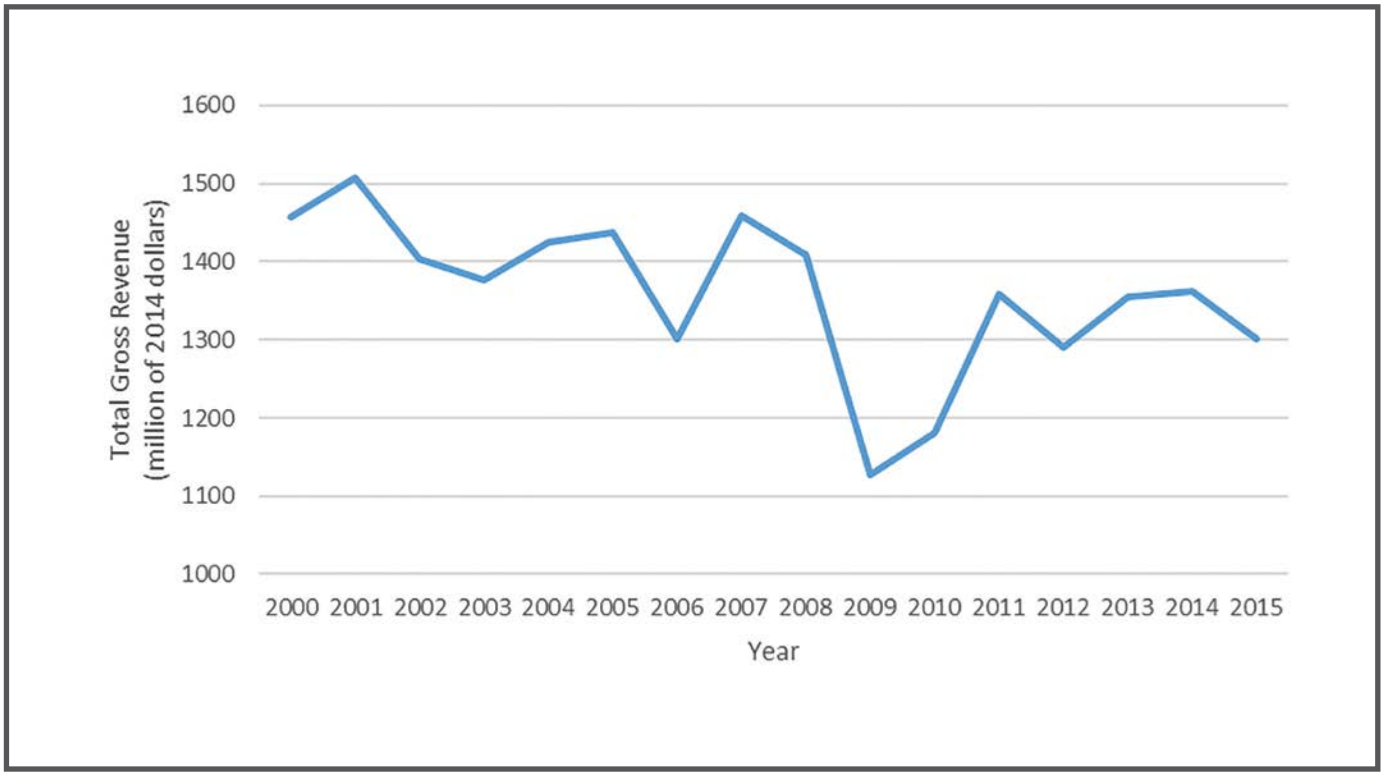

Figure 1: Total Gross Revenue from Agriculture in Riverside County, 2000–2015 (Source: Authors' elaboration, based on data from Riverside County Agricultural Commissioner Reports)

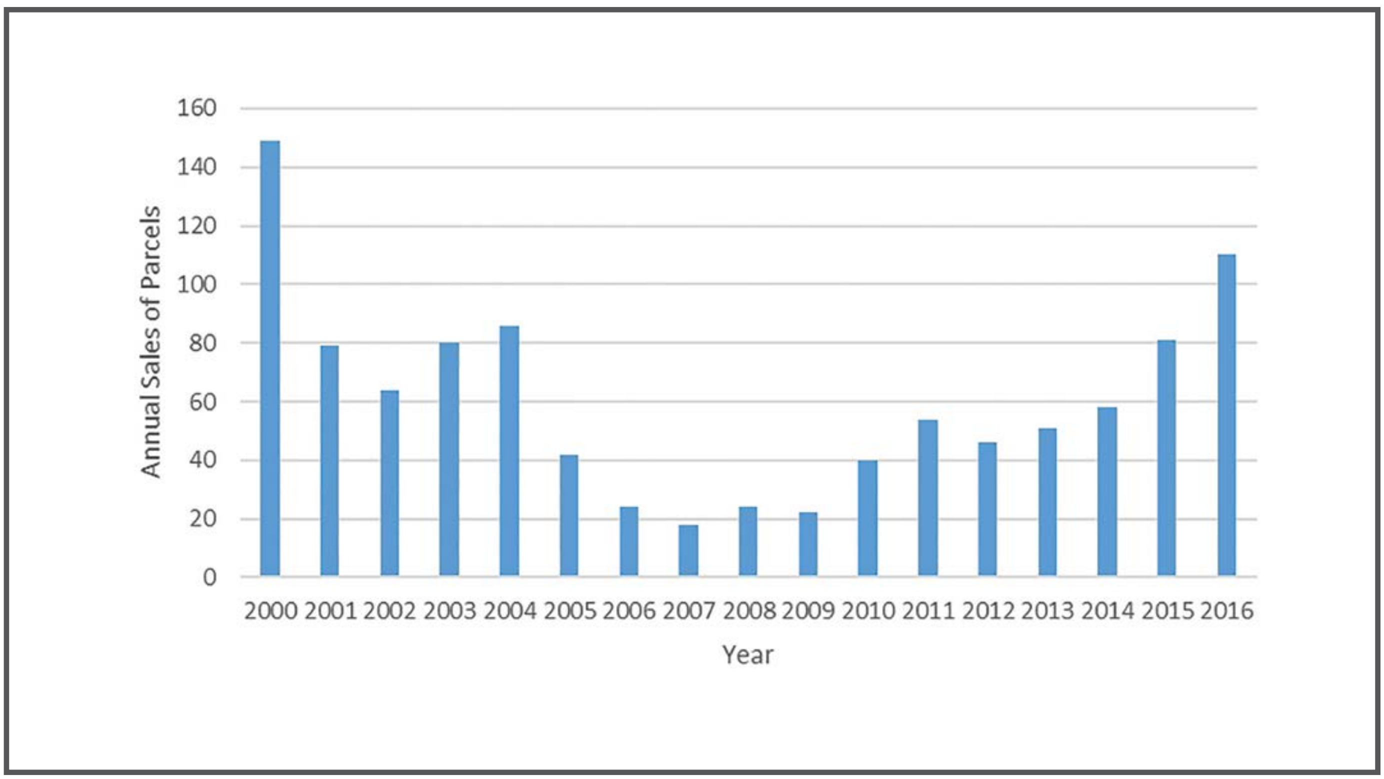

Figure 2: Total Parcels Sold in Dataset, 2000–2016 (Source: Authors' elaboration, based on data from Riverside County Assessor and ParcelQuest)

Table 1: Expected Impact of Several Control Variables on the Sale Likelihood and Value of Agricultural Land		
	Sale Likelihood	**Land Value**
Temperature mean	increase	decrease
Temperature variability	increase	decrease
Rainfall mean	decrease	increase
Rainfall variability	increase	decrease
Population	increase	increase
Population growth rate	increase	increase

Table 2: Summary Statistics and Variable Description					
Variable	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Variable Description**
Acre	28.65	37.10	0.19	466	Parcel acreage
sale_year	NA	NA	2000	2016	Year a parcel was sold
sale_acre_2014	20510.52	17985.44	60.82	80157.45	Sale price per acre in $2014
Slopegradd	12.35	15.10	1.00	53.00	Soil slope gradient
Usecode	2.38	1.06	1.00	5.00	Type of agricultural use, 5 levels
District	NA	NA	NA	4.00	Water district, 4 levels
pop_rate_10	0.12	0.14	-0.04	1.06	Population rate 10 years prior to sale
pop_mean_10	4.30	6.68	0.15	30.56	Population mean 10 years prior to sale divided by 10,000
ppt_mean_10	220.96	162.87	49.39	638.75	Annual precipitation mean 10 years prior to sale
ppt_cv_10	0.56	0.12	0.41	0.97	Annual precipitation variation 10 years prior to sale
tmax_mean_10	28.54	3.32	23.24	32.43	Annual maximum temp. mean 10 years prior to sale
tmax_cv_10	0.02	0.01	0.01	0.04	Annual maximum temp. variation 10 years prior to sale
tmax_mean_5	28.54	3.36	22.96	32.61	Annual maximum temp. mean 5 years prior to sale
tmax_cv_5	0.02	0.01	0.00	0.05	Annual maximum temp. variation 5 years prior to sale
ppt_mean_5	199.73	150.3	27.28	626.10	Annual precipitation mean 5 years prior to sale
ppt_cv_5	0.57	0.18	0.13	1.32	Annual precipitation variation 5 years prior to sale
pop_rate_5	0.07	0.49	-6.58	0.95	Population rate 5 years prior to sale
pop_mean_5	4.61	6.92	0.16	31.62	Population mean 5 years prior to sale divided by 10,000
ppt_normal	234.32	169.64	75.48	544.14	30-year precipitation normal
tmax_normal	28.51	3.19	23.68	32.00	30-year annual maximum temperature normal
sq_pop_rate_5	0.24	2.51	0.00	43.34	Square of population rate 5 years prior to sale
sq_pop_rate_10	0.03	0.08	0.00	1.12	Square of population rate 10 years prior to sale

Table 3: Logit Population-Averaged Panel Land Sales Analysis				
Dependent Variable = Likelihood of Land Sale	**Odds Ratio**	**Robust Std. Error**	**z-Value**	**Pr > |z|**
(Intercept)	0.075	0.313	-8.28	0.000***
ppt_mean_5	1.000	0.001	-0.36	0.717
tmax_cv_5	0.002	7.196	-0.88	0.379
ppt_cv_5	1.137	0.296	0.43	0.665
pop_rate_5	0.676	0.105	-3.72	0.000
sq_pop_rate_5	0.961	0.017	-2.35	0.019**
Land Use Code:				
Baseline=Avocado				
Citrus	0.790	0.129	-1.84	0.066**
General Irrigated	0.815	0.151	-1.35	0.176
Vineyard	0.669	0.153	-2.63	0.009***
Dates	0.785	0.184	-1.31	0.189
Water District:				
Baseline=CVWD				
EMWD	1.154	0.169	0.84	0.398
PVID	0.828	0.087	-2.18	0.029**
WMWD	1.075	0.160	0.45	0.655
Year Dummies:				
Baseline=2008				
2000	4.145	0.207	6.89	0.000***
2001	2.219	0.222	3.58	0.000***
2002	1.889	0.208	3.05	0.002***
2003	2.026	0.207	3.42	0.001***
2004	2.489	0.185	4.94	0.000***
2005	1.797	0.185	3.16	0.002***
2006	1.163	0.192	0.79	0.432
2007	0.718	0.218	-1.52	0.129
2009	0.748	0.209	-1.39	0.164
2010	1.038	0.198	0.19	0.851
2011	1.315	0.193	1.42	0.155
2012	1.616	0.189	2.54	0.011***
2013	1.606	0.210	2.26	0.024**
2014	1.730	0.197	2.79	0.005***
2015	2.479	0.221	4.11	0.000***
2016	2.667	0.247	3.98	0.000***
Wald chi2(28)	252.42***			
Pr > chi2	0			

Note: **p < 0.05, ***p < 0.01.

Table 4: Log-Linear Parcel-Level Ricardian Analysis				
Dependent Variable = Log Land Sale Value per Acre	**Coefficient**	**Robust Std. Error**	**t-Value**	**Pr(>|t|)**
(Intercept)	8.312	0.773	10.756	<2.2e-16***
ppt_mean_5	0.004	0.001	4.803	1.82e-06***
tmax_cv_5	-33.887	12.167	-2.785	0.005***
ppt_cv_5	-0.820	0.320	-2.563	0.011***
pop_rate_5	0.617	0.256	2.415	0.016***
sq_pop_rate_5	0.116	0.044	2.634	0.009***
Land Use Code:				
Baseline=Avocado				
Citrus	0.773	0.202	3.836	0.000***
General Irrigated	1.051	0.256	4.113	4.24e-05***
Vineyard	0.772	0.258	2.991	0.003***
Dates	1.495	0.338	4.418	1.11e-05***
Water District:				
Baseline=CVWD				
EMWD	-0.247	0.313	-0.789	0.430
PVID	-1.245	0.169	-7.381	3.41e-13***
WMWD	0.266	0.299	0.890	0.374
Year Dummies:				
Baseline=2008				
2000	0.971	0.711	1.367	0.172
2001	1.461	0.732	1.995	0.046**
2002	1.450	0.731	1.985	0.047**
2003	1.527	0.686	2.226	0.026**
2004	1.409	0.698	2.019	0.044**
2005	1.480	0.727	2.037	0.042**
2006	1.090	0.785	1.390	0.165
2007	1.575	0.689	2.287	0.022**
2009	1.354	0.708	1.914	0.056**
2010	0.995	0.693	1.436	0.151
2011	1.263	0.703	1.797	0.073*
2012	1.037	0.718	1.444	0.149
2013	1.509	0.709	2.128	0.034**
2014	1.162	0.695	1.673	0.095*
2015	2.026	0.730	2.774	0.006***
2016	2.030	0.744	2.730	0.006***
F-stat	14.903***			
Pr(>F-stat)	2.20e-16***			
Average MSE from cross-validation	0.79			

Note: *p < 0.1, **p < 0.05, ***p < 0.01.

Analysis of Alternative Levels of Facility Investment for Automatic Milking Systems

By Ryan C. Feuz and Dillon M. Feuz

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Abstract

In a classic labor versus capital tradeoff, some dairies are opting to install automatic milking systems (AMS). AMS have the potential to increase efficiencies but come at a cost. While the AMS units themselves are costly, the facility that houses them can often be a more significant expense. This paper analyzes the economics of installing AMS under three facility investment scenarios: minimal retrofit to existing facility, new open sided barn, and new fully enclosed barn. Results indicate that all three options are viable. Ultimately, the risk preferences and financial situation of the producer dictate which option should be chosen.

INTRODUCTION

Within the United States, milk is produced in all 50 states. However, the top five milk-producing states of California, Wisconsin, Idaho, New York, and Pennsylvania account for over half of the total production. The total number of milk cows has remained fairly constant over the past 25 years (1994–2018), only decreasing 1%. However, pounds of milk produced per cow over that time period has increased 42%. This trend continued throughout 2018 as total milk production climbed to a record high of 2.18 billion pounds (USDA, 2019).

Contrasting this increase in production have been decades-long decreases in per-capita demand. In 1975, the average American drank roughly 30 gallons of milk annually, while presently per-capita annual consumption has fallen to about 18 gallons (USDA, 2018a). This paints a bleak picture for many producers within the industry. Falling per-capita consumption with increased production results in excess supply and relatively low milk prices. According to the Livestock Market Information Center (LMIC), the Class III milk price has averaged $16.44/cwt. from 2008–2018, with less than a $0.07/cwt. annual increase over that time period (LMIC, 2019). This has led to tight or negative profit margins for many producers and has been the main factor in driving less profitable producers out of the industry. From 2008–2018, the USDA (2018b) reported that the number of licensed dairy farms in the United States decreased by 35%. Dairies surviving in the industry are getting larger on average and are chasing increased efficiencies to combat the low profit margins.

Another factor strongly influencing the dairy industry is an ongoing labor shortage. The U.S. labor economy is strong, with wages and employment in many categories reaching record highs in 2018 and 2019. Higher wage rates put increased pressure on the already tight dairy profit margins. The U.S. dairy industry relies heavily on immigrant labor. According to a national dairy labor survey conducted by the National Milk Producers Federation (Adcock, Anderson, and Rosson, 2015), immigrant labor accounted for 51.2% of the U.S. dairy labor pool in 2013. Tightening regulations surrounding immigrant labor only further intensifies the pressure on the already difficult dairy labor situation. Additionally, even if immigrant laborers are readily available it is becoming increasingly difficult for dairy farmers to compete with other industries for these laborers.

As in all industries, the firms that are most innovative are the ones that survive. As U.S. dairies strive to increase efficiencies to improve profit margins and manage the scarcity in labor, many consider implementing automatic milking systems (AMS). These robotic systems are a classic capital for labor tradeoff and for some dairies are proving to be a successful way to innovate and manage the labor shortage problem within the industry. AMS have the potential to improve efficiency by increasing pounds of milk per cow, decreasing pounds of feed required for a pound of milk, and greatly increasing pounds of milk per hour of labor. However, these potential increases in efficiency come at a cost—specifically, the cost of the robots, facilities to house the robots, and annual maintenance and repairs to the robots and facilities. Do the potential efficiency gains outweigh the additional cost?

The objective of this paper is to compare the financial impact of adopting AMS with little or no other management change but under three different barn design scenarios: minimal retrofit to existing facilities, new open sided milking barn, and new fully enclosed barn designed to optimize cow comfort and free flow to the AMS. Specifically, we will determine static (no risk) net annual financial impact and total change to cash flow for each scenario; we will also introduce risk through stochastic simulation and observe the impact on the net annual financial impact, as well as total change to cash flow.

LITERATURE REVIEW

AMS technology was developed to combat labor shortages on dairies in Europe in the early 1990s. The technology made its way to the United States in 2000 and has grown in popularity and implementation at an exponential rate. With the increasing popularity of AMS, there has naturally been a significant amount of research in this area.

Noting many simulation studies comparing AMS and conventional milking systems (CMS), Bijl, Kooistra, and Hogeveen (2007) used real accounting data to make the comparison using data from 62 Dutch dairy farms. They showed that dairy farmers with CMS had larger revenues (€7,899) than those with AMS—but no difference was found in the margin, partly due to the greater variable costs (€6,822) on CMS farms. The dairy farms were compared financially based on the amount of money that was available for rent, depreciation, interest, labor, and profit (RDILP). The CMS farms were found to have more money available for RDILP (€15,566) than the AMS farms. This difference was caused by larger fixed costs (excluding labor) for the AMS farms; larger contractor costs (€6,422); and larger costs for gas, water, and electricity (€1,549). However, when expressed per full-time employee, AMS farms had greater revenues, margins, and gross margins per full-time employee than did CMS farms. This resulted in greater RDILP per full-time employee (€12,953) for AMS farms compared with CMS farms. The authors concluded that farm managers should weigh the extra time acquired by automatic milking against the extra costs associated with AMS in making the decision of whether to implement AMS.

Salfer et al. (2017) noted that the limited economic analyses of CMS compared with AMS generally have shown AMS to be less profitable (see Dijkhuizen et al., 1997; Hyde and Engel, 2002; Rotz, Coiner, and Soder, 2003). However, they felt that recent advances in AMS technology, better understanding of optimum AMS management, higher labor costs, and limited availability of labor may change comparison results between AMS and CMS and felt that an updated simulation analysis was warranted. They developed partial budget simulations to model profitability of AMS compared with parlor systems for 120-, 240-, and 1500-cow dairies. They estimated that both the 120- and 240-cow AMS were more profitable than the parlor systems. However, with the larger 1500-cow dairy simulation they found that the conventional parlor system would be expected to be more profitable. Salfer et al. (2017) also found that the partial budget analysis was sensitive to various assumptions: milking labor cost, changes in milk production, and economic life of AMS. They conducted a break-even analysis on the labor cost assumption for the 1500-cow dairy and found that at a wage inflation rate of 1% and a 0.91 kg/day lower milk production with the AMS system, the break-even labor rate would be $27.02 per hour. However, if the farm was assumed able to achieve similar milk production between the two systems and wage inflation averaged 3% over the 30-year time horizon, the break-even wage rate would drop to $17.11 per hour. They also found that an economic life of 13 years or longer was required for an AMS to have a consistently positive net annual impact (depending on milk production per cow and labor cost) and that for every 227-kg increase in daily milk production per AMS, net annual income increased approximately $4,100.

Bentley, Schulte, and Tranel (2018) used a partial budget approach to determine the net financial impact on a 216-cow dairy of changing to AMS from CMS and estimated a positive net financial impact of $16,472 and a negative total change in cash flow of –$42,177. However, similar to Salfer et al. (2017), the researchers noted that their results were highly sensitive to various assumptions used in the partial budget they developed, specifically milk prices and milk production changes.

METHODS AND DATA

Much of the existing literature has demonstrated that the profitability of AMS can be quite sensitive to certain assumptions. Often the researchers have run multiple analyses for various size dairies or adjusted the sensitive assumptions to help present a range of plausible values. However, as noted by some past researchers, while the cost of AMS can be reasonably constant across all dairies, the level of investment in the facilities to house AMS can vary greatly. The greatest potential for efficiency gains from AMS are generally found when combined with fully enclosed barns where there is minimal human disturbance and cattle can free flow to AMS, feed, water, and resting areas. However, these types of fully enclosed facilities also represent the most significant investment. While many dairies have installed very similar AMS, they have chosen to invest in varying degrees of barn construction from minimally retrofitting existing facilities to perhaps constructing new cattle loafing areas to facilitate flow to the AMS. Others have chosen to construct fully enclosed new barns to house all milking cattle. To our knowledge, there have been no studies comparing AMS to CMS under different levels of facility investment. Are the most efficient fully enclosed barn facilities the most economical, or does some other level of facility investment have the potential for greater returns?

To answer this question, we use a partial budgeting framework similar to that used by Bentley, Schulte, and Tranel (2018). Their assumptions are updated to reflect the 2018 dairy market in the Mountain West states. The partial budgeting framework is used to calculate the static net financial impact, which is the sum of the positive financial impacts less the sum of the negative financial impacts and includes depreciation and interest costs associated with AMS and the barn to house the system. Change to total cash flow under three facility investment scenarios as well as the baseline CMS scenario is also determined. Following the static analysis, risk is explicitly introduced by allowing key parameters to vary stochastically over multiple iterations and observing the effect on the net financial impact, as well as change to total cash flow under the same three investment scenarios.

All three AMS scenarios assume a 144-cow dairy requiring two AMS. Each system is purchased for $190,000, with a useful life of 15 years, a salvage value of $40,000, and an estimated annual repair cost of $7,000. For the static analysis, historical 10-year averages (2009–2018) are used for milk price, feed price, and the interest rate. The interest rate used is the U.S. federal prime rate; a 2% and 3% markup are added to the prime rate for the AMS equipment and facility loans, respectively. The 10-year average of the prime rate is 3.5%; thus, for the static analysis the interest rate is 5.5% on the robots (seven-year loan), while for the barn construction the interest rate is assumed to be 6.5% (15-year loan). Table 1 contains additional assumptions for each scenario.

Scenario 1 represents a minimal retrofit to existing facilities, with cost of the facility retrofitting at $70,000. Scenario 2 involves the construction of a new open sided milking barn at a cost of $470,000. For Scenario 3 a new fully enclosed barn is constructed at a cost of $920,000. In addition to the change in initial capital outlay, milk productivity, feed efficiency, and labor savings all vary across the scenarios.

For the stochastic analysis, Palisade's @RISK risk-detection tool (Palisade, 2019) is used to fit distributions to milk price, feed price, interest rate, and milk production increase; results are then simulated over 10,000 iterations, and the effect on the annual net financial impact as well as the total change to cash flow is observed. Ten years (2009–2018) of annual data is used in fitting the distributions for milk price, feed price, and interest rate, while for the milk production increase we use a triangle distribution with a low, expected, and high value to model the distribution.

The assumptions in Table 1 are taken from Bentley, Schulte, and Tranel (2018), with updates made through discussions with dairy managers who had installed AMS and with input from AMS representatives in the Western U.S. dairy industry. Data for historical milk price as well as feed costs are obtained from the Livestock Marketing Information Center (LMIC, 2019).

The partial budgeting framework taken from Bentley, Schulte, and Tranel (2018) is a standard partial budget analysis with both positive impacts (increased incomes and decreased expenses) and negative impacts (increased expenses and decreased incomes). With the conversion to AMS, the efficiency increases have the potential to both increase income and decrease some expenses. Under a two times per day milking system it is reasonable to expect increased milk production, which in turn results in increased income (Bentley, Schulte, and Tranel, 2018). Additional increases to income can be expected due to the increased precision management abilities afforded by the AMS computer system. The herd management software included with AMS has the ability to track and record rumination data, milk conductivity, and cow activity, and the computer can send out timely reports to managers to alert them of any significant changes or potential problems. The software heightens mastitis and heat detection ability. Precision feed rationing is also a possibility and can produce additional feed efficiency gains. All of these benefits of the herd management software ultimately lead to increased value to the operation and represent an increase in income. Some expenses are also expected to decrease with AMS.

One of the largest incentives to switching to robotics is the decrease in labor required to run the dairy. AMS typically results in large reductions to daily milking labor, with moderate increases to records management. Substantial decreases to labor expenses are therefore expected when converting to AMS. Additional labor savings and feed waste savings may also be obtained with Scenarios 2 and 3. It is typical on many Western U.S. dairies to feed the cattle along feed bunks that are not enclosed and that are fully exposed to the weather. This results in wasted feed from rain, snow, sunshine, and birds. Covering the feeding area in an open sided barn reduces much of this feed waste, and feed waste is completely eliminated in fully enclosed barns. Many dairies that have invested in AMS and have invested in covered or fully enclosed feeding areas have also invested in robotic feed pushers that keep the feed pushed up for cattle to access. This results in additional labor savings, and at least some dairies with fully enclosed facilities and robotic feed pushers have gone from feeding twice a day to one time per day— further adding to the labor savings.

The final positive impact is the annual increased value to quality of life of the producer. This value is different in that it is not easily monetized and can vary drastically from one individual producer to another. Just because it is not easily valued does not mean that it is of little merit, however. Producers often cite this positive impact to their quality of life as the number one reason for switching to AMS. Dairymen have traditionally worked long hours with little to no downtime. AMS allow milking labor times to be cut back and provide a more flexible schedule to mangers. This flexibility is a large positive impact; however, because it cannot be universally assigned a consistent value between operators, the net annual financial impacts reported in this paper do not consider this benefit.

On the negative impact side of the budget, AMS bring several added expenses. The largest expenses associated with AMS are the cost of the robot itself and the facility to house the robot. The added depreciation and interest expenses of AMS are significant. Like all machinery, AMS require annual maintenance and repairs that also add to the expenses. Additionally, while partially offset by feed efficiency gains, producing greater milk quantity using AMS requires additional feed. Thus, there is an increased feed cost associated with AMS. As mentioned previously, records management increases under AMS and carries an added cost for the management labor. While admittedly small, there is also often a noticeable increase in utilities needed to run an AMS dairy as compared to CMS.

Cash Flow Analysis

The summation of the positive and negative impacts results in the calculation of net annual financial impact. This value is an important indicator for producers to consider because it gives a good indication of expected payoff (profit) annually of implementing AMS. However, the net financial impact taken alone gives the operator no indication of the expected ability of the farm to successfully manage cash flow. Thus, a separate cash flow analysis is performed for each scenario and must be considered together with the net financial impact when making the conversion to AMS decision. In this analysis, the change in total cash flow is reported from the partial budget analysis. No assumptions are made as to whether the overall cash flow for the dairy is positive or negative after AMS installation.

RESULTS

Static Analysis

Using the assumptions outlined previously, we calculate the net financial impact as well as the total change to cash flow under the three investment scenarios and summarize the results in Table 2.

Looking at the results displayed in Table 2, initially we would conclude that without accounting for risk (variability in parameters), Scenario 3 has the greatest potential for positive increases in net financial impact as well as the least negatively impacted cash flow. The negative cash flow changes can be overcome by increasing the AMS loan from seven years to nine, 10, or 11 years depending on the scenario. Since the fully enclosed barn also has the potential for the greatest efficiency gains, this would be the most desirable investment strategy. However, the static analysis only represents what type of returns we might expect "on average." To better understand the distribution of the net financial impact and total change to cash flow, we must allow key parameters to vary stochastically.

Stochastic Simulation

Summary statistics for the simulated annual net financial impact and total change to cash flow are presented in Tables 3 and 4, respectively. Cumulative distribution function (CDF) graphs of the three simulated scenarios for the annual net financial impact and total change to cash flow are presented in Figures 1 and 2, respectively.

Observing the values in Table 3, it is apparent that similar to the static analysis, the greatest net annual financial impact is with Scenario 3, the fully enclosed barn. However, it is also apparent that this scenario has the most variability with the largest standard deviation and the greatest range. Conversely, while Scenario 1 has a smaller net annual financial impact, it also has the least amount of variability. Which investment strategy is best? It depends on an individual's risk/return tolerance or preference.

From the CDF graph in Figure 1, almost one-third of the time (32.5%) the net annual financial impact will be expected to be negative for Scenario 3 as compared to only 22% of the time for Scenario 1. However, for Scenario 3, 18.3% of the time the net annual financial impact is expected to increase more than $30,000, or $250 per cow being milked. Scenario 1 is almost never (2% of time) expected to be above this level.

Based on the assumption of paying off the AMS loan in seven years and the construction of the new barn loan in 15 years, all three of the scenarios are expected to see a negative change in cash flow (Table 4 and Figure 2). That negative change is expected to be the least with Scenario 3 and the greatest with Scenario 1. Scenario 3 does have the greatest amount of variability in changes to cash flow, and Scenario 1 has the least amount of variability. However, there is only a 4% chance that the changes to cash flow will be positive in Scenario 1. It is not shown here as part of the analysis, but changes to cash flow can be neutralized by increasing the AMS loan payout period from seven to 11 years for Scenario 1, 10 years for Scenario 2, and nine years for Scenario 3.

Thus far, only Scenarios 1 and 3 have been discussed; they represent the extremes in terms of lower expected returns with lower risk versus higher expected returns with higher risk. However, this does not imply that these are the only two viable scenarios to consider. Scenario 2 represents a scenario with a moderate expected return and a moderate amount of risk. All three scenarios may fit what an individual producer wants to do and provide different levels of capital investment and risk that may match up better with an individual producer's financial position and risk appetite.

CONCLUSIONS

The results of the simulated analysis indicate that we would expect all three scenarios to have a positive annual financial impact. However, this positive financial impact must be considered together with the projected total annual change in cash flow. Before any producer makes the switch to AMS, consideration must be given as to whether the farm has the ability to absorb the projected negative impact to cash flow until the loans can be paid down. Restructuring the loan payout period can alleviate the negative change to cash flow consequences.

Comparing the simulated results for annual net financial impact with the results from the simulated change to cash flow between the three scenarios would suggest that there is no "one size fits all" answer to what scenario is best. The minimal retrofit option (Scenario 1) may be less risky in terms of net financial impact (smaller standard deviation), but it also represents the option that we would expect to have the greatest negative impact on the ability of the farm to manage cash flow. While the fully enclosed barn has the potential for the greatest net annual financial return with the least projected negative impact to annual cash flow, it also has the largest amount of expected variability. As one might expect, the open sided barn's performance would lie somewhere in between the minimal retrofit and fully enclosed barn.

After noting the ambiguity above, how then would a producer make the investment decision? Ultimately, it would depend on the individual risk appetite of the producer, the current interest rate environment, current financial position, and additional producer preferences (i.e., quality of life emphasis). When choosing to implement AMS, there is no dominant strategy for choosing which type of facility investment scenario is best. A dairy's current financial position may constrain the decision to one of the scenarios with lower upfront costs. Does the dairy have adequate liquid assets to be able to handle a down payment? What other debt is already on the balance sheet, and how could adding to the debt affect the dairy's financial position? These types of questions would guide producers in assessing whether a certain scenario would be financially feasible to undertake.

As for the timing of such a decision, the current and forecasted condition of the dairy market and economy in general plays a large role. With an ongoing labor shortage in the dairy industry, AMS may appear attractive to many dairymen. However, producers must consider the overall health of the dairy industry when determining if, and when, the operation should invest in robotics.

The individual preferences of producers would likely dictate both the level of facility investment and the timing. As dairy operations evolve and time passes, an operator's preferences and needs change. One dairyman may not mind spending the majority of their time milking cows, while another may prefer to make the switch to AMS and enjoy spending time engaged in other management duties, including leveraging the power of the computer tracking system provided through AMS. Each producer will place a different value on their time and find more or less enjoyment in performing various tasks. Aside from financial feasibility, these differences in producer preferences may ultimately have the largest impact on the AMS facility investment decision.

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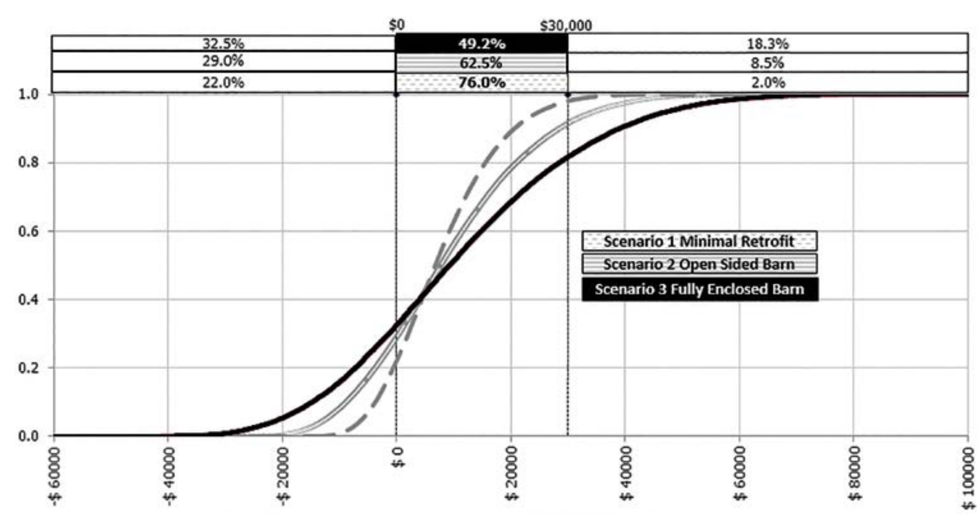

Figure 1. CDF of Net Financial Impact for Three AMS Scenarios

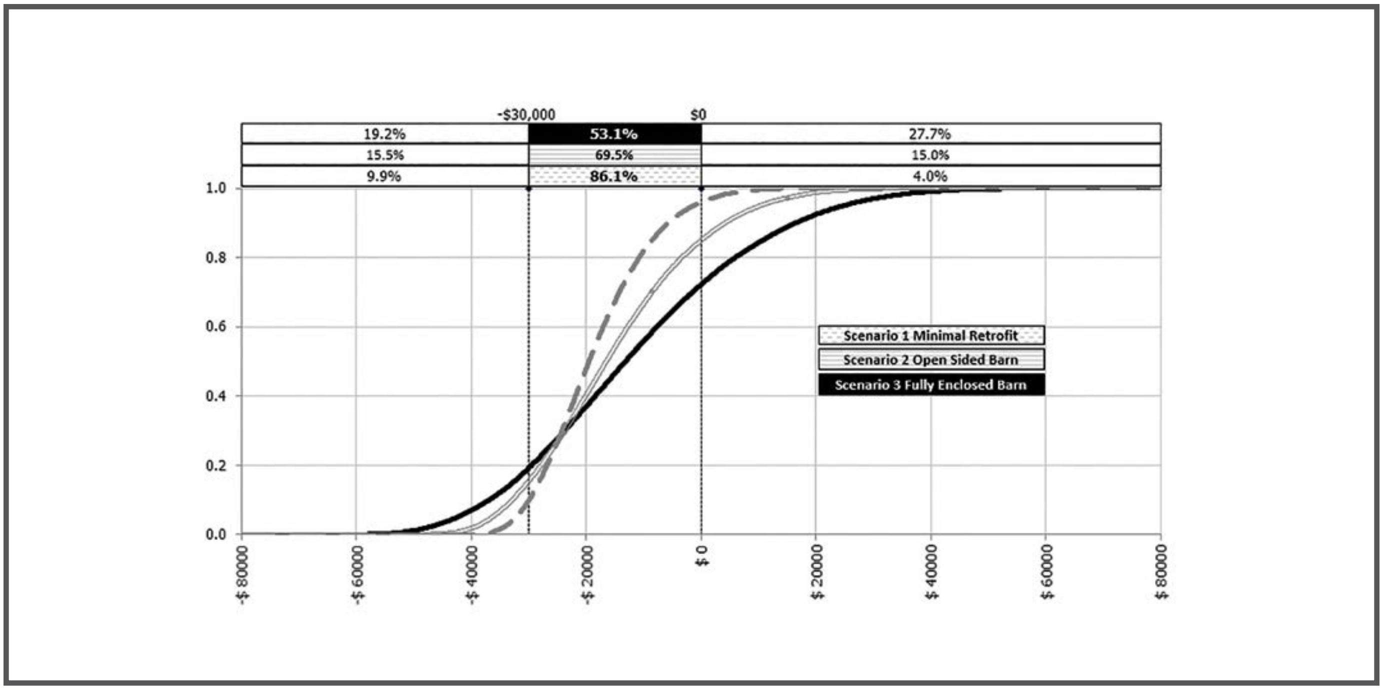

Figure 2. CDF Total Change to Cash Flow Under Three AMS Scenarios

Table 1. Assumptions in the Partial Budget Simulation for Each Scenario

	CMS[a]	AMS[b] Scenario		
Variable	**Value**	**1**	**2**	**3**
Current Hrs. of Milking Labor (hrs/day)	9			
Anticipated Hrs. of Milking Labor (hrs/day)		3	2	2
Current Hrs. of Heat Detection (hrs/day)	0.65			
Anticipated Hrs. of Heat Detection (hrs/day)		0.40	0.30	0.25
Labor Rate ($/hour)	$15			
Reduced Feeding Labor (hrs/day)		0.0	0.3	1.0
Lbs of Milk per Cow per Day	72.5			
Percentage Milk Production Increase		3%–9%	7%–14%	12%–20%
Lbs of Dry Matter per lb of Milk	0.64	0.62	0.60	0.58
Feed Waste & Efficiency Savings ($)		2,860	10,431	22,377
Increased Feed Costs for Added Milk ($)	28.54	7,132	9,537	13,601
		Mean	**Min**	**Max**
Milk Price ($/cwt)	28.54	17.91	10.49	26.44
Feed Cost per lb of Dry Matter ($/lb)	0.02	0.12	0.09	0.17
Prime Interest Rate (%)	199.73	3.53	3.25	5.35

[a]CMS = Conventional Milking Systems; [b]AMS = Automatic Milking Systems

Table 2. Static Comparison of Net Financial Impact and Total Change to Cash Flow Under Three AMS Scenarios		
Scenario	**Net Annual Financial Impact**	**Total Changes in Cash Flow**
1. Minimal Retrofit	$6,659.00	–$19,263.00
2. New Build: Open Sided	$9,145.00	–$14,388.00
3. New Build: Fully Enclosed	$10,485.00	–$10,365.00

Table 3. Summary Statistics for Simulated Net Annual Financial Impact for Three AMS Scenarios			
	Scenario 1 Minimal Retrofit	**Scenario 2 Open Sided Barn**	**Scenario 3 Fully Enclosed Barn**
Mean	$7,752	$8,914	$10,824
Standard Deviation	$9,485	$14,333	$20,613
Coefficient of Variation	1.22	1.61	1.90
Minimum	–$42,483	–$36,094	–$59,729
Maximum	$48,118	$64,999	$86,835

Table 4. Summary Statistics for Simulated Total Change to Cash Flow Under Three AMS Scenarios			
	Scenario 1 Minimal Retrofit	**Scenario 2 Open Sided Barn**	**Scenario 3 Fully Enclosed Barn**
Mean	–$18,539	–$15,300	–$11,559
Standard Deviation	$9,428	$14,211	$20,409
Coefficient of Variation	0.51	0.93	1.77
Minimum	–$51,437	–$53,182	–$68,368
Maximum	$21,526	$40,005	$63,260

Working for Peanuts: Acquiring, Analyzing, and Visualizing Publicly Available Data




By Jason K. Ward, Terry W. Griffin, David L. Jordan, and Gary T. Roberson

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Abstract

Data visualization has become important to farm management and commodity marketing during recent price and weather phenomena. Accessing and evaluating United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) data via software tools empowers rural property professionals to mitigate risk. Data acquisition and visualization examples include days suitable for fieldwork (DSFW) during peanut planting and harvest in 11 peanut producing states. The overall objective was to share techniques to access and analyze publicly available data. Specific objectives were to demonstrate software tools to define most active dates for field activities, estimate DSFW during most active dates for each state, and assess DSFW time trends. Analytic results are important for machinery selection and acreage allocation. Software tools have been made available for readers to use in their own applied research.

INTRODUCTION

Farmers and researchers utilize fieldwork probabilities either explicitly or implicitly. Producers question if they can "get over" their acreage during the time window most conducive to the success of producing crops. Some will consider recent history and others will calculate coverage rate based on their specific machines, but both will likely include some additional time to account for adverse field conditions. Weather conditions such as rainfall and temperature impact the soil surface, thereby affecting the ability of machinery to conduct needed fieldwork during critical time windows. Evaluating days suitable for fieldwork (DSFW) can provide producers with input into machine and land management decisions.

Analyses of long-term DSFW data have been reported for individual states including Arkansas (Griffin, 2009; Griffin and Kelley, 2010), Illinois (Schnitkey, 2010), Indiana (Parsons and Doster, 1980), Iowa (Hannah and Edwards, 2014; Rosburg, Griffin, and Coffey, 2019), Kansas (Buller, 1992; Carls and Griffin, 2016; Williams and Llewelyn, 2013), Kentucky (Shockley and Mark, 2017), Mississippi (Spurlock, Buehring, and Caillavet, 1995), and Missouri (Massey, 2007), as well as across production regions for corn (Gramig and Yun, 2016; Irwin and Hubbs, 2018) and cotton (Bolton et al., 1968; Griffin and Barnes, 2017). An exhaustive search of the literature revealed no availability of peanut DSFW information suitable for farm management.

Several studies presented how farmers utilize fieldwork probabilities to determine optimal machinery sizing (Griffin, Buschermohle, and Barnes, 2015; Rosburg and Griffin, 2018; Schrock, 1976) and crop allocation (Kastens, 1997; Carpenter, Gerit, and Massey, 2012; Hannah, 2001). In peanuts, Jordan et al. (2018) conducted a survey of growers in Virginia, North Carolina, and South Carolina. The authors report that grower-respondents needed two days to dispense protectant products including fungicides and pesticides over approximately 250 acres per application. In total, each producer dedicated 18% of their time in the growing season to protectant application. This study builds upon Griffin (2009) and Griffin and Barnes (2017) by applying analyses specifically to peanut production plus providing software tools to assist researchers to conduct their own analyses. Griffin and Barnes (2017) evaluated DSFW specific to sizing planters and cotton pickers across 13 cotton producing states. Griffin (2009) provided step-by-step guidance in acquiring DSFW data from the United States Department of Agriculture (USDA) by using Arkansas as an example. Soil and weather conditions are essential to timely peanut field operations, especially harvesting. Adequate capacity was essential to the complete logistics of digging, harvesting, drying, and transportation (Meeks et al., 2005). Digging capacity for four- or six-row equipment has been estimated as 30–40 acres per day in ideal conditions and perfect field efficiency (Jordan et al., 2017). Harvest capacity has been estimated as 15–20 acres per day for four- and six-row pull-behind equipment. Advances in modern machine telematics allow specific working rates for machines and field processes to be calculated at increasing granularity and accuracy. Even with new tools to assess machine field capacity and field efficiencies, updated DSFW values created a context against which to compare the machine itself to its ability to perform in the larger production system.

The objectives of this analysis were to (1) update "most active" dates for peanut planting and harvest field activities, (2) calculate DSFW occurring within the most active date ranges for each peanut producing state, and (3) analyze collected DSFW data for trends over time. To supplement the objectives, a farm management example was described indicating how risk averse peanut growers may use these results obtained via modern software tools.

METHODS AND MATERIALS

The USDA National Agricultural Statistics Service (NASS) defines "most active" dates to plant and harvest specific crops as those days falling within the 15th and 85th percentile of reported crop progress (USDA NASS, 2010). A similar method was applied to extract the most active fieldwork period from regularly published annual survey data rather than rely on the decade-old "most active" dates reported by USDA NASS (2010) in a static report based on the previous 20 years of crop progress data. Using live data allowed the calculation of most active periods for states that were not previously reported as producing peanuts. Updated most active date ranges were determined from the most recent four years of available data, where available. The number of the calendar week marking the start and end of the most active dates for each state was determined using the same 15% and 85% crop completion criteria defined by USDA NASS. It should be noted that "most active" dates are not necessarily the best timing for highest yields, but when farmers are most actively conducting the selected operations.

DSFW data was collected for 11 states from 1995–2018 for planting and harvest. Days suitable and crop progress were reported weekly throughout the growing season and were cataloged as part of the annual survey datasets for their respective years. The described analysis retrieved data only after it was made available as part of an annual survey dataset. It should be noted that data was not available for two peanut producing states, Florida and Texas, prior to 2014. For each year, the number of weeks with DSFW available during most active times were evaluated to ensure that data was reported for each week. For each year, weekly DSFW were summed during most active planting and harvest dates. Resulting sums were analyzed and four descriptive plots were created for each peanut producing state. The four plots were a probabilistic analysis of DSFW per each week at the 15th, 50th, and 85th percentile; fieldwork progress for each week; and histograms representing the total number of DSFW available historically during "most active" planting and harvest windows.

The probabilistic analysis plot described variability in DSFW within and across growing seasons. Progress charts were standard data products the USDA produced weekly and were used in this analysis to visualize the most active period. The histograms were designed to indicate the historical flexibility in DSFW for each key field operation. A tight distribution indicated less flexibility than a wide distribution.

Annual trends in DSFW by state were evaluated to determine if significant changes in fieldwork days were detected over the 24-year period being analyzed. The linear trend of the data was assessed to determine if values of the variable in question increase, decrease, or remain unchanged over time. Specifically, the slope of estimated trend lines was examined to determine if they were statistically significantly different from zero during planting and harvest. Trend lines were estimated using ordinary least squares (OLS) in an R statistical environment (R Core Team, 2019).

If no change over time was found, more confidence exists in expecting a range of known DSFW for future years. However, if change was observed in the past, then expectation exists for potential changes along the same direction in the future. When the trendline slopes were not considered statistically significant, then the trendlines were interpreted to not be changing over time. When the null hypothesis that the estimated slope was not statistically different than zero was rejected, then the slope of the line was considered non-zero.

In addition to examining if trends were significant, structural changes were assessed by a Chow test (Chow, 1960) from contributed R package "strucchange" (Zeileis et al., 2002). Florida and Texas did not have sufficient data available and were therefore omitted from being evaluated by the Chow test.

The complete R script used in this analysis and resulting color plots are available for download as a GitHub repository (Griffin and Ward, 2019). The R script ingests the most recent data available; results may differ from those presented in this manuscript, because additional data is provided by USDA NASS. See the Appendix for additional information on specific commands used to access the data.

RESULTS AND DISCUSSION

Eleven U.S. states produce sufficient peanuts to be considered a "peanut producing state" such that USDA NASS reports data. For the 2018 production year, Georgia peanut farmers harvested 47.5% of the total U.S. acreage (Table 1) at 650,000 acres. The next two largest peanut producing states represent nearly one-fourth of the U.S. production. Alabama produced 11.8%, and Texas with 145,000 harvested acres produced 10.6% of harvested area. Of the 11 peanut producing states, New Mexico harvested the least area at 5,500 acres or 0.4% of total U.S. harvested area. North Carolina ranked fifth in harvested acres with 98,000 in 2018.

The most active time to plant peanuts in most states lasted three or four weeks. In North Carolina, the most active planting time lasted four weeks, while in Arkansas it lasted six weeks. Most states took six weeks to harvest during their most active period. The states with the shortest most active planting time had the longest most active harvest dates. In Arkansas, most active harvest time lasted six weeks, while in South Carolina it lasted eight weeks.

The most active planting times begin first in Arkansas and Florida during week 17 and last in New Mexico in week 20. All states finished the most active planting time in weeks 22–23. Most active peanut harvest begins first in Florida during week 38 and last in Oklahoma in week 42. In Florida, the most active peanut harvest dates end in week 42, the same week that Oklahoma most active harvest dates begin. Peanut producing states finish the most active harvest dates by end of week 46.

For each of the 11 peanut producing states, four plots were created with the software tool. As an application example, consider peanut field operations in North Carolina. Although only North Carolina results are presented, figures from all states are available at the project GitHub site (Griffin and Ward, 2019). Figure 1 displays long-term probability of observed DSFW at 15th, 50th, and 85th percentiles in North Carolina. For each week, the 15th (dotted green line), 50th (dashed red line), and 85th (solid black line) percentiles were presented representing the range of observed fieldwork days since 1995 for all states except Texas and Florida, for which data was not available before 2014. The y-axis ranges from 0–7, the number of calendar days per week. The x-axis is the week number expressed as week of year such that week number two begins on Sunday following January 1. Farm management decisions to allocate acreage to a crop or size equipment for target acreage can be made using information from this graph of fieldwork probabilities, particularly number of DSFW between the 15th and 50th percentiles. Variability over the calendar year was noted as DSFW was decreased at the beginning and ending of the field season.

Figure 2 depicts the empirical cumulative three-year average of when farmers planted (solid line) and harvested (dashed line) peanuts in North Carolina. Crop progress begins at 0% and ends at 100% completion, although the data usually ceased to be reported after 95% complete. The intersection of the horizontal lines at 15th and 85th percentiles with the empirical cumulative crop progress indicates the range of "most active" fieldwork. Some nonlinearities at extremities of reported data were observed, typically as data approached 100% complete. Percent completion data was compiled from field reports and may have been corrected if initial reports were overestimated. Functionally, the more linear portion between 15% and 85% completion was the most important part of the reported data and expresses to completion rate of fieldwork.

Figures 3 and 4 display histograms of the total number of DSFW during most active planting and harvest periods, respectively, for each year data was available. The y-axis indicates the number of years that had a specific number of days suitable during most active period. The x-axis reports the number of DSFW during the most active period. The y-axis label includes the number of years that data was available for the respective state (data for some states was omitted due to not reporting DSFW for all weeks for a given year during most active dates).

Over the 24 years of planting data in North Carolina, growers never had more than 25 days to conduct fieldwork (Figure 3). The most common number of DSFW for planting was 21–22 days, which occurred 7 out of the 23 years of available data. North Carolina farmers had more than 40 harvest work days only once during the 24-year data period (Figure 4). Most of the time producers had 30–35 days to conduct field operations during the most active peanut harvest times.

Peanut harvest is a complex, multi-pass series of field operations involving digging, desiccation, and harvest. Weather conditions during digging and before combining are correlated to both yield and quality. The modern peanut digger-shaker-inverter (DSI) is responsible for the first phase of peanut harvest. The DSI uses a sharp blade to fracture the soil around the pods and a shaker section, often a chain mechanism, to lift the peanut pods from the soil and shake off as much soil as possible. Finally, the DSI will invert the peanuts so the pods face up and deposit the peanut vines and pods into windrows. Inversion of the peanuts allows separation of the pods from the soil and allows air circulation to improve the field drying or curing phase. Windrows are formed typically between two to seven days, to dry without necessitating forced air drying and improve threshing performance during combining. Windrows require additional management if precipitation occurs after digging or if soil conditions were wet during digging. Wet or muddy windrows are "lifted" or "fluffed" to expedite drying, which increases risks of reduced harvestable yield due to shaking pods loose from the vines. In addition, pod quality is adversely impacted from excessive moisture. Weather conditions similar to that needed for fieldwork are advantageous for in-field drying. Experiencing DSFW during the critical time between digging and combining is important to protecting yield and quality. Therefore, some of the available DSFW for harvest is committed to in-field drying and not just operating equipment in the field.

Changes in Fieldwork Probability Over Time

Results of planting and harvesting trend analysis are presented in Table 2. There were no significant trends in the total number of days available for fieldwork since 1995 in all peanut producing states, including both planting and harvest. Trendline slopes were tested but none were statistically different from zero at any conventional confidence level. As an example, the OLS trendline slope of North Carolina planting DSFW from 1995–2018 was estimated as −0.09 but was not statistically significantly different from zero. In this example, it was not expected that North Carolina had any fewer or additional DSFW in the past as it does in the present. Time trends were tested, and no structural changes were detected for any states during planting or harvest time periods. Therefore, no substantial trend or structural breaks in DSFW were observed over the 24-year time period.

FARM MANAGEMENT IMPLICATIONS

Variability in DSFW has farm management implications. Using North Carolina DSFW data and conservative parameters from Jordan et al. (2017), a hypothetical example is described under a range of observed weather with respect to peanut acreage that can be planted and harvested with typical equipment on 100 acres. The equipment performance rates for an equipment complement are estimated assuming a 10-hour workday. Row spacing and ground speed will change estimated equipment performance rates; these estimates do not include additional time allowances for transport of equipment among fields. Tables 3 and 4 present minimum, maximum, and specific percentiles of DSFW. These values can be compared to calculated equipment coverage rates to determine if an operation has enough machine capacity.

The rules of thumb for a four-row equipment complement estimate three days for digging and an additional six days for combining 100 acres. Windrow drying between these field operations could range between two and seven days. In practice, harvest field operations are likely concurrent with other field operations, meaning that digging is occurring a few days ahead of combining and some fields are drying as others are being combined. In total, all harvest field operations could require from 11–16 days to harvest 100 acres. During the six-week harvest time, North Carolina peanut growers had at least 19.3 DSFW (Table 4). The most DSFW observed in North Carolina was 39.5 days. The median DSFW was 31.9, while the 15th percentile was 26.5 (Table 4). Producers in North Carolina estimated that they spent 15 days to dig and 25 days to harvest during the 2017 growing season (Jordan, 2018). The total of 40 estimated days for harvest fieldwork put the producers in the position needing all of the historically available field days to complete their fieldwork.

Equipment performance rates and the calculated DSFW for different levels of weather risk indicate that a four-row equipment complement is adequate for a hypothetical 100 acres of peanuts even with exceptionally few DSFW. A total of 200 acres would fall at the upper edge of the equipment range even at the median number of DSFW. Some or part of the equipment complement could be sized up to six-row to create some additional capacity, or a second four-row combine could be added—which would increase capacity in the slowest field operation and help protect from the loss of working days as a result of machine failure if only one combine were available. Harvest date decisions require producers to decide between expected weight gain in immature pods and yield loss from shedding mature pods. Yield penalty from not harvesting at optimum maturity is highly variable among cultivars and years, so specific yield penalties are difficult to generalize since maturity must be assessed discreetly. Sizing equipment complements should include capacity to harvest as close to optimum as possible, so excess harvest capacity may be justified.

CONCLUSIONS

Publicly available data can be mined for useful farm management information. Free, open-source technology tools and scripted data analysis can allow for rapid visualization of useful data—in this case the number of days available for fieldwork. Weather uncertainty impacts farmers' decisions regarding acreage and equipment complements. Knowledge of weather probabilities, as represented by DSFW, allows farmers to improve their ability to make optimal decisions regarding peanut acreage, planters, and digging equipment. Over long periods of time, no discernible trends in increased or decreased numbers of days to plant or harvest peanuts were detected. Therefore, peanut growers can expect the yearly DSFW to be within the range of previous observations.

Most active fieldwork times were calculated for each of the 11 peanut producing states by observing when producers were between 15% and 85% complete with field operations. Most active days ranged widely among states, starting between weeks 17–20 and ending between weeks 22–24 for planting. Harvest most active days started at weeks 37–42 and ended at weeks 42–46.

Crop progress reports within the most active days for fieldwork were used to calculated DSFW for each of the 11 peanut states. The results varied across states and based on the selected probability distribution. The key point was to not size equipment so that field capacity is at the maximum DSFW. Equipment complements decisions should include some amount of weather risk. Given negligible change over time, historically calculated state-specific DSFW allows better estimation of risk.

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APPENDIX

The full R script used in this analysis is available as a GitHub repository (Griffin and Ward, 2019).

The three required contributed packages to R, usdarnass, tidyverse, and strucchange, are called in lines 5, 6, and 7 (Figure A). The lower and upper bounds for Figure 1 are set in lines 9 and 10. The user can change these to other levels such as the 25th and 75th percentiles by changing the 0.15 and 0.85 to 0.25 and 0.75, respectively. Future researchers may desire for the analysis to include data from the most recent years. In that case, the currentYear parameter in line 11 should be changed from 2018 to the year of most recently available planting and harvest data. The “most active” dates have been assumed to be the 15th and 85th percentile crop progress. The analyst may decide to widen or restrict these ranges and can do so by changing the parameters in lines 12 and 13.

Users must request an API key from USDA NASS to enter into the R script on line 15 before gaining access to data (Figure B). Lines 17 to 19 are likely the most efficient script to access the number of harvested peanut acres since 2014 at the state level. Data for earlier years is available and can be requested by replacing the 2014 with another year. The “>=” before the year is interpreted as “greater than or equal to” such that 2014 was included in the data request. Other crops could be requested by replacing “PEANUTS” with the crop such as “COTTON” (however, it should be noted that other minor differences may require the analyst to update other portions of the script).

Lines 21 to 30 format the data. Line 21 subsets the data to only include the current year (set to be 2018 in line 11). Line 22 removes commas as thousands place in numbers. Line 23 forces all numbers to be interpreted as numbers. Line 24 creates a new variable calculated as percent of total harvested acres. Line 25 creates a new data frame named “dat2” from the four columns. Line 26 instructs the new data frame to be interpreted as a data frame. Line 27 assigns names to each data column. Line 28 creates a new data frame and omits rows of data where state name was “Other States.” Line 29 creates a data column as rank of U.S. total acreage. Line 30 saves the data as a *.csv file named “dat4table1.csv.”

Figure 1 in the text was created by lines 94 to 106 using ggplot() function from ggplot2 contributed package to R (Figure C). The ggplot2 package is part of the tidyverse set of packages, so it was not required to call it individually in the first few lines of the R script. Lines 95 to 97 instruct the software to create a line graph with numerical week of year on the x-axis and value (DSFW per week) on the y-axis, grouped as the percentiles set in lines 9 and 10 plus the median 50th percentile. Line 105 saves the graph as “graph.png.”

```
 4 # installs required packages
 5 library(usdarnass) # negates necessity for API
 6 library(tidyverse) # ggplot() and gather()
 7 library(strucchange) # Chow test
 8
 9 min.prob<-0.15 # lower bound DSFW, a "bad" year,  FYI 0.50 is median
10 max.prob<-0.85 # upper bound DSFW, a "good" year
11 currentYear<-2019 # ignores 2020 for now
12 begin=15 # percent progress of beginning of most active dates
13 end=85 # percent progress of ending of most active dates
```

Figure A. R Code to Call Contributed Packages and Set Parameters

```
15 nass_set_key(key = "XXXXXXXX-XXXX-XXXX-XXXX-XXXXXXXXXXXX", overwrite =
   FALSE) #replace XXXX with key
16
17 peanutHarvest<-nass_data(year=">=2014", agg_level_desc = "STATE",
18                          short_desc = "PEANUTS - ACRES HARVESTED",
19                          reference_period_desc = "YEAR")
20
21 dat<-subset(peanutHarvest, year==currentYear)
22 dat$value<-as.numeric(gsub(",", "", dat$Value))
23 dat$value<-as.numeric(dat$value)
24 dat$percent<-round(dat$value/sum(dat$value)*100,1)
25 dat2<-cbind(dat$state_name,dat$value, dat$percent, dat$state_fips_code)
26 dat3<-as.data.frame(dat2)
27 colnames(dat3)<-c("State", "acres", "PercTotal", "STATE_FIPS")
28 dat4<-subset(dat3, State!= "OTHER STATES")
29 dat4$Rank<-rank(-as.numeric(as.character(dat4$acres)))
30 write.csv(dat4,"dat4table1.csv")
```

Figure B. R Code for Accessing USDA NASS Data via API

```
 94 ggplot() +
 95     geom_line(aes(x=dat4DSFW$WOY, y= dat4DSFW$value,
 96     group=dat4DSFW$variable,  linetype=dat4DSFW$variable,
 97     color=dat4DSFW$variable), size=1.) +
 98 scale_y_continuous(breaks = round(seq(0, 7, by = 1),1), limits=c(0,7)) +
 99 xlim(0, 52) + guides(fill=guide_legend(title=NULL)) +
100 labs(y="Days per week", x="Week of year", caption="Source: USDA NASS") +
101 labs(colour = "Percentile") +
102 scale_color_manual("", values=c("darkgreen", "darkred", "black")) +
103 scale_linetype_manual("", values=c("dotted", "twodash", "solid"))+
104 theme_bw()
105 ggsave(paste("1DSFW", state, "graph.png", sep=""), width=6, height=4,
106 units="in", dpi = 600)
```

Figure C. R Code for Creating Figure 1

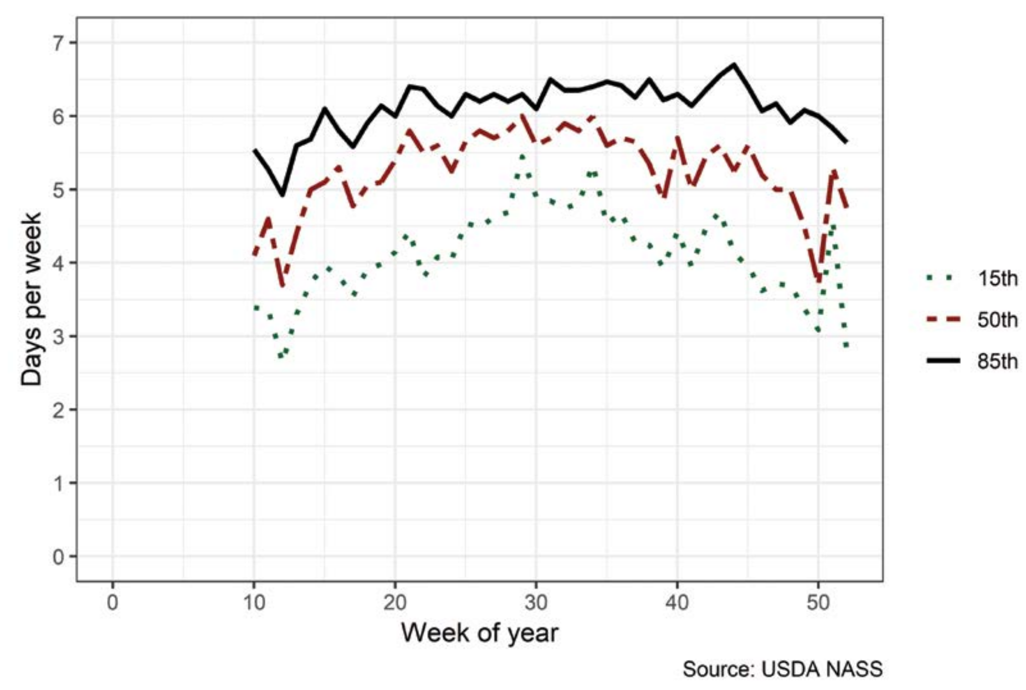

Figure 1. Long-Term DSFW Percentile by Week of Year in North Carolina (1995–2018)

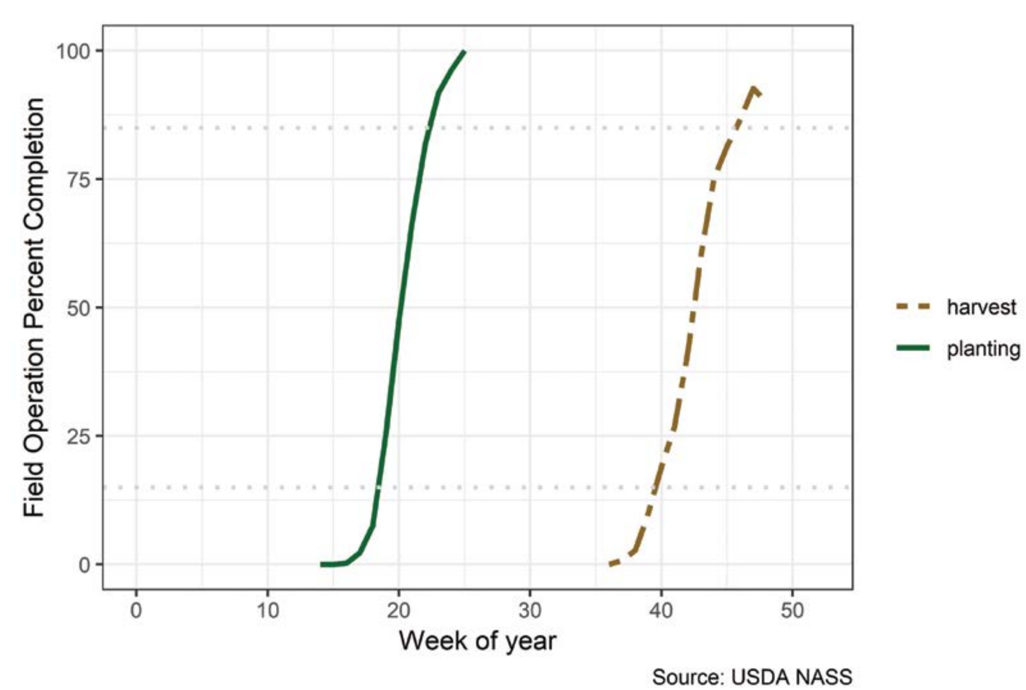

Figure 2. Empirical Average North Carolina Planting and Harvest Fieldwork Progress by Week of Year (2015-2017). Note: Most active fieldwork days occurred between the 15th and 85th percentile of fieldwork completion.

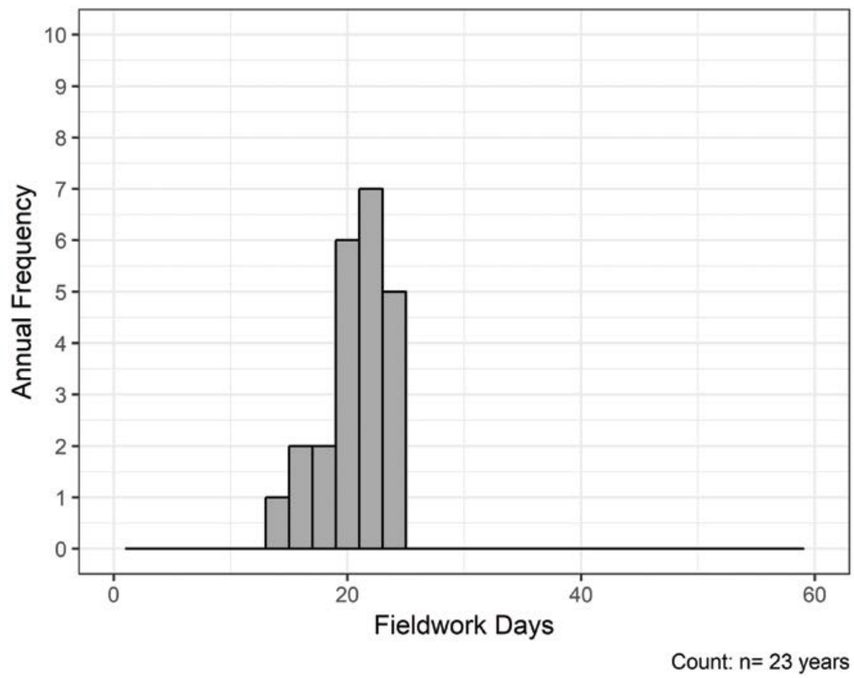

Figure 3. Number of Fieldwork Days During Planting in North Carolina (1995–2018)

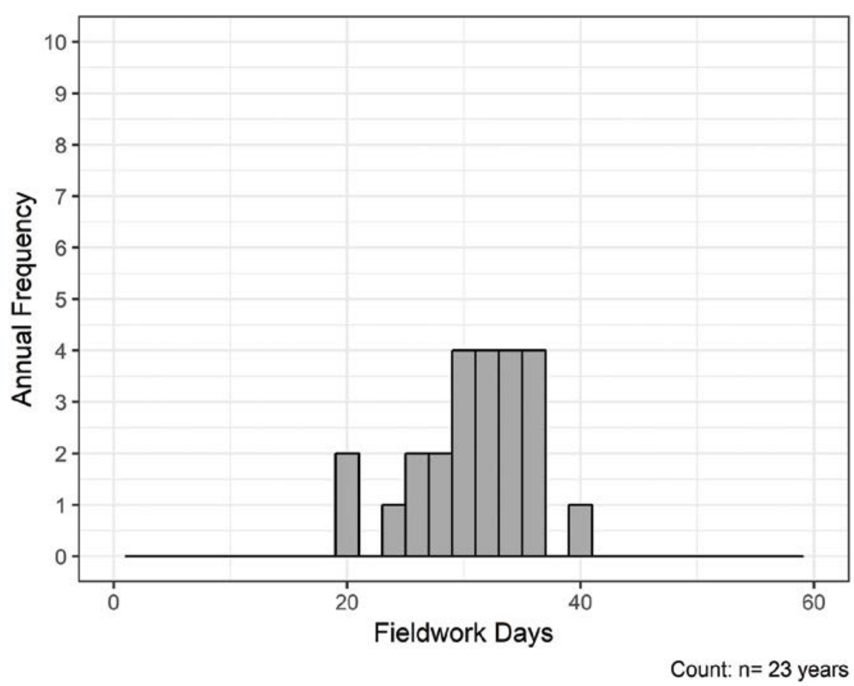

Figure 4. Number of Fieldwork Days During Harvest in North Carolina (1995–2018)

Table 1. 2018 USDA NASS Harvested Acreage and Most Active Fieldwork Dates

State	Area Harvested (Acres)	Rank	% U.S. Total	Begin Plant	End Plant	Begin Harvest	End Harvest
				Calendar Week[a]			
Alabama	162,000	2	11.8	18	23	39	45
Arkansas	23,000	9	1.7	17	22	40	45
Florida	140,000	4	10.2	17	21	38	42
Georgia	650,000	1	47.5	18	22	39	45
Mississippi	24,000	7.5	1.8	18	23	39	45
New Mexico	5,500	11	0.4	20	24	41	47
North Carolina	98,000	5	7.2	19	22	41	46
Oklahoma	15,000	10	1.1	18	22	42	46
South Carolina	82,000	6	6.0	19	22	40	47
Texas	145,000	3	10.6	19	22	41	47
Virginia	24,000	7.5	1.8	19	22	40	44

[a]Numerical calendar week; week 2 starts the Sunday after January 1.

Table 2. Slope of Cumulative DSFW During Most Active Field Operations (1995-2018)

State	Planting		Harvest	
	Slope	p-Value	Slope	p-Value
Alabama	−0.08	0.60	0.15	0.48
Arkansas	−0.23	0.11	−0.10	0.57
Florida	−0.55	0.39	0.21	0.43
Georgia	−0.07	0.42	0.11	0.44
Mississippi	−0.04	0.77	0.03	0.91
New Mexico	−0.07	0.35	0.13	0.29
North Carolina	−0.09	0.32	−0.03	0.81
Oklahoma	0.00	0.99	0.18	0.29
South Carolina	−0.10	0.11	−0.04	0.79
Texas	1.96	0.34	-1.20	0.60
Virginia	0.00	0.99	−0.07	0.56

Table 3. Historic Number of Days Suitable by Percentile for Peanut Planting (1995-2018)					
State	Percentile				
	Min	15th	50th	85th	Max
Alabama	17.5	27.4	32.3	35.7	40.2
Arkansas	19.9	24.0	29.0	32.6	39.6
Florida	27.8	29.4	31.7	31.8	31.9
Georgia	22.0	24.7	28.3	30.1	32.9
Mississippi	21.2	23.6	29.8	33.5	36.6
New Mexico	25.2	30.8	33.5	34.1	34.9
North Carolina	14.1	17.6	21.4	23.5	25.0
Oklahoma	11.2	18.7	25.1	28.9	30.2
South Carolina	17.6	20.5	23.5	24.4	25.3
Texas	11.3	16.2	22.2	24.4	26.0
Virginia	12.2	15.5	20.1	22.8	25.1

Table 4. Historic Number of Days Suitable by Percentile for Peanut Harvest (1995-2018)					
State	Percentile				
	Min	15th	50th	85th	Max
Alabama	24.1	31.1	39.4	43.5	48.2
Arkansas	19.5	25.1	34.2	37.0	41.0
Florida	30.1	30.4	30.7	31.3	32.0
Georgia	29.6	31.9	40.2	42.9	45.9
Mississippi	15.8	28.0	37.6	42.1	45.8
New Mexico	33.1	39.0	45.8	46.9	48.4
North Carolina	19.3	25.8	31.7	35.5	39.5
Oklahoma	12.4	18.9	28.2	31.4	33.1
South Carolina	30.2	38.3	45.6	49.6	51.0
Texas	29.6	33.3	40.4	43.0	45.2
Virginia	16.2	23.4	26.0	30.4	33.6

Quality Effects on Kansas Land Price Trends




By Mykel R. Taylor, Lucas Sudbeck, Christine Wilson, and Jisang Yu

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Abstract

This study aims to determine if there are differences in the rate of appreciation for high- versus low-quality land. Using aggregated parcel sales data from Kansas, two price series are generated that reflect crop productivity as measured by the Natural Resources Conservation Service. A seemingly unrelated regression (SUR) is estimated to determine if there is a difference in the rate of change of land prices for high- and low-quality land. Results suggest that high-quality land appreciates at a faster rate than low-quality land. The analysis also reveals that during periods of price decline, high- and low-quality land depreciate at roughly the same rate. This study is of interest to land appraisers, farmers, and others interested in investing in land for the long run.

INTRODUCTION

Changes in agricultural land values are of interest to farmers, lenders, and other investors. For farmers in particular, land is typically the largest asset, in dollar value, that they own. Therefore, the appreciation rate of their land is of interest as they apply for loans, evaluate their financial position, and plan for wealth transfer to succeeding generations.

Over the past several years, we have seen crop income move from extremely high to very low—and land values have adjusted to those changes in income. In Kansas, land values steadily increased from 2008–2014, which corresponded to an increase in commodity prices. However, land values began to decline starting in 2015—reflecting the downturn in commodity prices and fall in net farm income.

When the opportunity to purchase land presents itself, farmers—the biggest purchasers of farmland—must decide if a piece of ground is a good investment. Often, they consider the relative productivity of the ground in that purchase decision. Is high-quality ground worth the purchase price because of its potential productive capacity and income generation, or is it a wiser purchase to buy lower-quality ground at a lower price?

Previous literature has examined land values in the context of what factors affect land prices, such as productivity of the land, parcel size, interest rates, location, and irrigation (Alston, 1986; Taylor and Brester, 2005; Baird, 2010; Burt, 1986; Sampson, Hendricks, and Taylor, 2019). However, with the exception of the Chicago Federal Reserve Bank's survey (2019) that focuses on high-quality farmland, most data series are not specific to a qualify reference.

In this analysis, we look at a long-term pair of price series that reflect the appreciation and subsequent depreciation in land values from 1989–2018. The analysis reveals that high-quality land increases in value at approximately twice the rate as low-quality land, suggesting that demand for high-quality land was stronger among buyers. However, there is no statistical difference between high- and low-quality land value changes during periods of declining land values, as seen in the past several years.

DATA AND METHODS

The data on land values used in this study was collected from the Kansas Department of Revenue's Property Valuation Department. Each observation is a single property sale with information on the final sale price and characteristics of the tract of land sold. Characteristics include parcel size, land cover percentage (i.e., proportion of the parcel that is non-irrigated cropland, irrigated cropland, and pasture), and a soil-based crop productivity index measured by the Natural Resources Conservation Service. The crop productivity index gauges the crop growing potential of each soil found on the parcel of land.

We use an acre-weighted version of the crop productivity index to proxy for the overall productivity of the parcel sold. Each parcel in the dataset is described by the different soils and the corresponding quality rating of the soils that comprise each parcel. As such, we are able to weight the productivity rating of the parcel by the percentage of soil found in the parcel. This weighted-average soil productivity index provides a proxy for the overall productivity of the parcel and can be used to compare productivity across parcels.

Parcels that included more than 50% irrigated land were excluded from the analysis due to price differences based on water availability, which we could not measure. The raw data was cleaned to remove parcels smaller than 40 acres and sales prices below 1% and above 99% of the price distribution. The observations that remain are considered market transactions. These individual land sales were aggregated by crop productivity index to create a quarterly, statewide quality-based price series. We used the highest 25% crop productivity index parcels to create the "high-quality" price series and the lowest 25% to create the "low-quality" index.

Figure 1 shows the high-quality and low-quality price series starting in 1989 and ending in 2018. From the figure, an upward trend in land values is apparent from 2008–2014, at which point both series begin to decline. This pattern corresponds with the pattern of net farm income over the same period. The question our analysis aims to answer is whether or not the value of the high-quality land grows (declines) at the same rate of change as that of the low-quality land grows (declines).

To answer this question, we estimate the following equations:

$$y_{ht} = \beta_{h0} + \beta_{h1}Post_t + \beta_{h2}Trend_t \times Pre_t + \beta_{h3}Trend_t \times Post_t + \varepsilon_{ht} \quad (1)$$

$$y_{lt} = \beta_{l0} + \beta_{l1}Post_t + \beta_{l2}Trend_t \times Pre_t + \beta_{l3}Trend_t \times Post_t + \varepsilon_{lt} \quad (2)$$

where subscript t indicates quarter; y_h and y_l are land values of high-quality and low-quality lands, respectively, measured in dollar per acre; and *Pre* and *Post* are indicator variables that represent pre-2014 quarters and post-2014 quarters. The exact break point is the second quarter of 2014, where the price of land turns from a positive trend to a negative trend. The two equations are motivated by the structural test scheme developed by Chow (1960).

We jointly estimate equations (1) and (2) using a seemingly unrelated regression (SUR) method to test whether the changes in "pre" and "post" periods are statistically different between high-quality and low-quality lands. The SUR method considers cross-equation correlations for the estimation of the standard errors (Zellner, 1962). In other words, we test (a) $\beta_{h2} = \beta_{l2}$ and (b) $\beta_{h3} = \beta_{l3}$, and the SUR estimation of the two equations provides variance-covariance estimates to conduct the statistical tests of our interest.

RESULTS

The results of the SUR estimation reveal a difference in the rate of change in prices for high-quality versus low-quality land. The coefficients from the estimation are presented in Table 1, alongside standard errors and t-test results of the difference between the rate of change of high-quality and low-quality land. We provide the results from the estimations with both levels and logs of land values as the dependent variable to give a measure of the change in dollars per acre and in percentage terms.

The trend in land values for high-quality land during the period of increasing prices (from 1989 through the second quarter of 2014) is \$13.70/acre per quarter. The rate of change for low-quality land during the increasing price period is \$6.77/acre. The difference between them (\$6.93/acre) is statistically significant at the 1% level. This means that high-quality land was increasing at a faster rate (more than double) than low-quality land was increasing during the same period. The results are similar for the log price regression, where the difference of 1.13% is statistically significant at the 10% level.

The period of decreasing prices, from the third quarter of 2014 to the end of 2018, shows a different relationship between high-quality and low-quality land prices. The estimates from the SUR model indicate that high-quality land has been decreasing at a rate of –\$32.45/acre, while low-quality land has decreased over the same period at a rate of –\$28.78/acre. The difference between the two rates of change, \$3.67/acre, is not statistically significant. This means that both low- and high-quality land are decreasing at approximately the same rate of change. The estimates for the log prices are similar, with a statistically insignificant difference between the two trends.

IMPLICATIONS

The findings of this analysis suggest that differences in land quality do affect the rate of appreciation in land values over time. They also indicate that those differences may vary by whether or not prices are increasing or decreasing. Over the period 1989–2014, Kansas land values for high-quality land were increasing at approximately twice the rate of low-quality land. However, during the period from the third quarter of 2014 to the end of 2018, when land values were declining, the rates of change were approximately equal.

A possible explanation for this difference in the rate of change in land values over time is the observed shift in acres in Kansas from wheat to corn. According to the United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS), the harvested wheat acres in Kansas have declined 24% over the period 2015–2019 (USDA-NASS, 2019). During that same period, harvested corn acres increased 53%. Farmers were shifting acres of high-quality land to corn production, while the low-quality land was typically still being used to raise wheat. Corn production on high-quality land meant that the value of that land relative to low-quality land was increasing, as shown in our analysis.

These results reveal that the land market does differentiate by land quality in terms of overall price paid for land and the rate of appreciation. As an overall investment, high-quality land appreciates at a faster rate than low-quality land. For land investors, this willingness to pay more for high-quality land becomes greater as the ability to bid more for land occurs (i.e., periods of high net farm income). The widening of the difference between high- and low-quality land prices suggests that high-quality land, although more expensive to purchase initially, has a higher return to landowners over time.

There is no measurable difference in the rate of change between the high- and low-quality land prices as they decline, however. This may be due to the relatively short period of observations in our dataset. It is possible that differences in the rate of change between high- and low-quality land would appear if the price downturn lasted for a longer period of time. This remains to be measured and provides motivation for future research on the appreciation and depreciation rates of different land classes and how different factors in the farm economy affect the rates.

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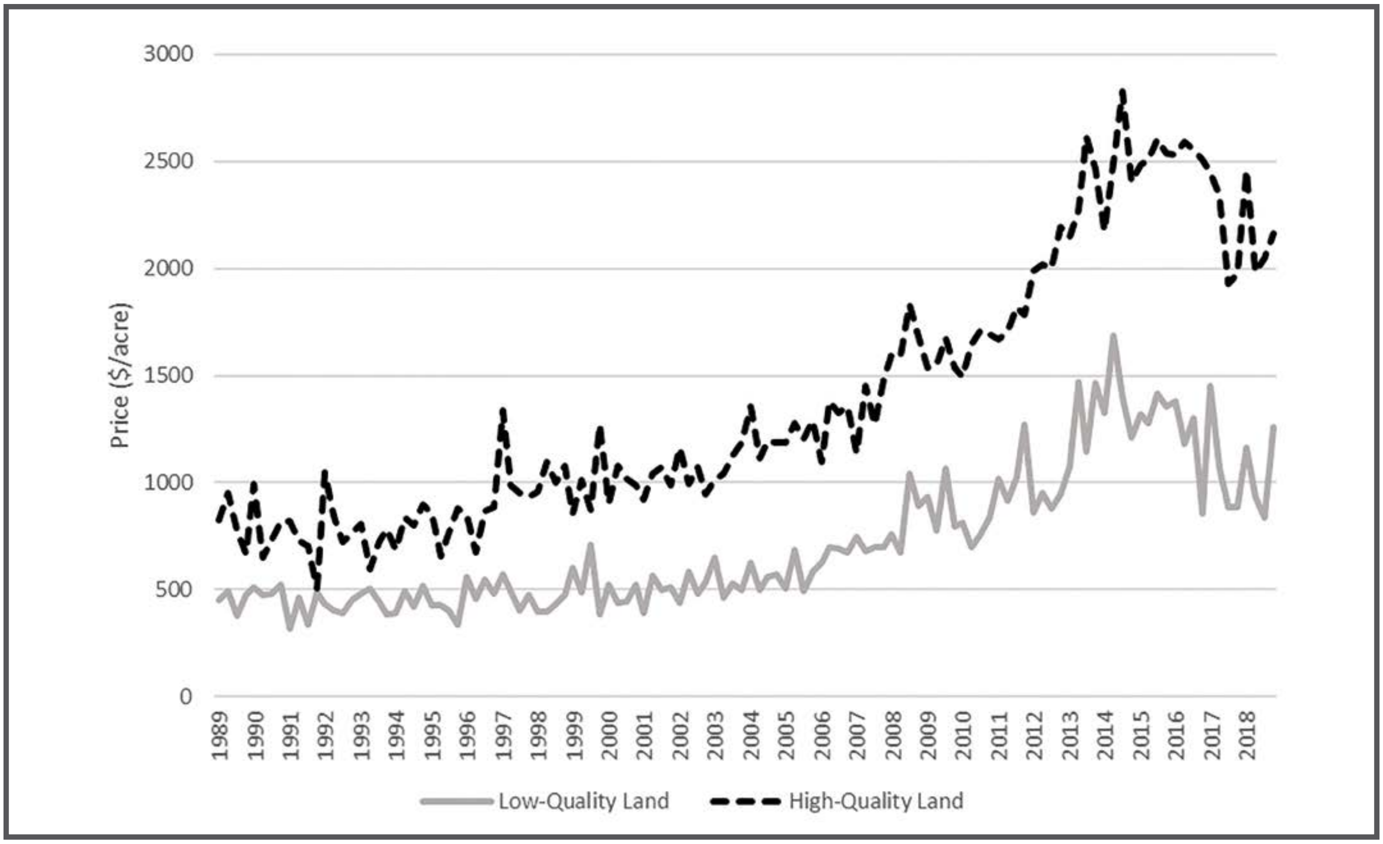

Figure 1. Kansas Land Prices (1989–2018)

Table 1. Seemingly Unrelated Regression (SUR) Estimation Results

	Levels			Logs		
Variables	**High Quality**	**Low Quality**	**Diff (a-b)**	**ln (High Quality)**	**ln (Low Quality)**	**Diff (c-d)**
	a	b		c	d	
Trend (Pre)	13.70***	6.770***	6.934***	0.0111***	0.00994***	0.0113*
	(0.681)	(0.512)	(0.558)	(0.000455)	(0.000620)	(0.001)
Trend (Post)	−32.45***	−28.78***	−3.668	−0.0140**	−0.0246***	0.0106
	(8.362)	(6.289)	(6.848)	(0.00558)	(0.00761)	(0.008)
Post Dummy	5,496***	4,123***		2.873***	3.944***	
	(930.2)	(699.6)		(0.620)	(0.846)	
Constant	496.2***	274.8***		6.475***	5.859***	
	(40.03)	(30.10)		(0.0267)	(0.0364)	
Observations	120	120		120	120	
R-squared	0.892	0.784		0.902	0.81	

Note: Standard errors in parentheses. "Pre" is quarter before the second quarter of 2014.

***p < 0.01; **p < 0.05; *p < 0.1.

Predicting Nitrogen Fertilizer Prices

By Gregory Ibendahl

Gregory Ibendahl is an Associate Professor in the Department of Agricultural Economics at Kansas State University.

Abstract

Fertilizer is a major expense item for farmers, currently accounting for 20% of crop production expense. Because fertilizer is a major crop production expense and the price can vary greatly throughout the year, the ability to predict future fertilizer prices could greatly help farmers control their cost of production by signaling to farmers the optimal time to purchase fertilizer. The ability to predict fertilizer prices would also help farmers choose a crop mix for the coming year since some crop enterprises are more sensitive to changing fertilizer costs. This paper builds a fertilizer price prediction model that is based on both the corn futures prices and the price of oil in order to come up with a more accurate prediction model that can help farmers lower their fertilizer cost. Corn futures prices are a representation of fertilizer demand, whereas oil prices are a representation of fertilizer supply. The resulting model has an R-squared value above 0.8, indicating that it is possible to predict monthly fertilizer prices.

INTRODUCTION

Although fertilizer prices the past three years have been less expensive than they were for the period from 2012–2015 (DTN, 2019), fertilizer is still a significant expense for most grain farms. Fertilizer currently accounts for 15% to 20% of total crop production expenses in Kansas, as shown in Figure 1. Fertilizer expense as a percentage of crop expenses varies across the state and is lowest in western Kansas. The 15% of production expenses for fertilizer is within historical percentages.

Figure 2 shows the average dollar expense for fertilizer per acre for east, central, and western Kansas. Figures 1 and 2 are both based on data from the Kansas Farm Management Association (KFMA). The values shown in Figure 2 have been adjusted for inflation by the Consumer Price Index to allow a more meaningful comparison of past costs to today. As shown in this figure, fertilizer cost per acre has varied greatly across time. Fertilizer costs ranged from \$20 to \$30 per acre for much of the late 1980s, 1990s, and early 2000s. However, fertilizer costs per acre started rising around 2005 and peaked in 2012 when in eastern Kansas the fertilizer cost per acre was near \$80.

The higher dollar per acre fertilizer cost can be attributed to three factors. The first factor is higher fertilizer prices. As will be shown later, the fertilizer price is closely tied to the price of oil, and this period saw higher oil prices. The second factor is a shift in the crop mix to more corn. Corn requires a high level of nitrogen fertilizer, which means this crop is more expensive to grow. Third, the higher grain prices leading up to 2012 meant that it was profitable for farmers to fertilize at higher rates. Since 2012, fertilizer costs per acre have declined for the same reasons they increased. Even with this recent decline, fertilizer costs per acre are nearly double what they were in the 1990s (in real dollars).

With profitability for grain farms limited by low grain prices, producers need to manage their expenses very closely if they want to be profitable. Fertilizer is a good candidate for analysis, given that fertilizer is a major expense item for every crop farm. If farmers could predict fertilizer prices six months or more in advance, they could purchase their fertilizer at the low price points of the year and also adjust their crop mix to account for years when fertilizer was either higher or lower than normal. Also, the ability to predict fertilizer prices would help farmers with their planning as they work with lenders to obtain operating loans.

The purpose of this paper is to show a method that predicts fertilizer prices so that farmers can make crop mix decisions and time their fertilizer purchases to improve profitability. The model developed here uses a combination of the oil price and the corn futures price. The oil price helps represent the supply side for fertilizer, whereas the corn futures price represents the demand side of fertilizer.

DATA AND MODEL

Predicting nitrogen fertilizer prices is possible because the price of anhydrous ammonia is positively correlated with the price of both oil and corn. Nitrogen is one of the most important fertilizers in the production of corn, grain sorghum, and wheat; therefore, predicting anhydrous ammonia prices will cover a majority of the fertilizer expenses on a farm. Other nitrogen fertilizers start with ammonia, so forecasting anhydrous ammonia provides an indication of prices for the other nitrogen products. In addition, anhydrous ammonia is positively correlated with other fertilizers besides nitrogen—so correctly predicting anhydrous ammonia will give some indication of the price direction of other fertilizers.

Anhydrous ammonia is positively correlated with the corn price and the oil price because these two products represent something about the demand and supply of anhydrous ammonia fertilizer. Economic theory tells us that higher prices for an output will cause producers to produce more by using more of the production inputs. Thus, higher corn prices lead to more nitrogen fertilizer per corn acre (i.e., increased demand for nitrogen fertilizer). Also, a higher corn price will shift more acres to corn (which uses nitrogen) and fewer acres to soybeans (which doesn't need nitrogen fertilizer). Figure 3 shows the relationship between the national anhydrous ammonia price and the national corn price since 2010 on a monthly basis. This monthly correlation is 0.79. National anhydrous ammonia prices come from the fertilizer reports published by Progressive Farmer (DTN, 2019). National monthly corn futures are from Investing.com (Investing.com, 2019).

The supply side of anhydrous ammonia is represented by the oil price. Ammonia is produced as a result of a catalytic reaction from burning natural gas (the hydrogen) and the nitrogen in the air. Thus, the expectation is that lower natural gas prices should lead to more production of ammonia. However, the correlation between monthly natural gas prices and monthly anhydrous ammonia prices is low (0.14). This may be because natural gas prices are more volatile than other oil products. Figure 4 shows the historical monthly prices of anhydrous ammonia and natural gas. Even when allowing for a lag in the natural gas price, the correlation between natural gas prices and anhydrous ammonia prices remains low.

With monthly prices, the use of oil as opposed to natural gas provides a stronger correlation to anhydrous ammonia. Oil and natural gas can be substitutes for each other in certain situations and have a 0.58 correlation. The correlation between oil prices and anhydrous ammonia prices is 0.63. However, a visual inspection of oil and anhydrous ammonia historical prices indicates that anhydrous ammonia prices tend to lag oil prices. This is not surprising because ammonia producers need some time to adjust production to account for changes in their input prices. Testing of various oil price lags revealed that a nine-month lag in oil prices provided the best fit to anhydrous ammonia prices. With this lag, the correlation between oil prices and anhydrous ammonia increased to 0.82. Figure 5 shows the historical monthly prices of anhydrous ammonia, oil, and the oil price lagged by nine months.

Model to Predict Anhydrous Ammonia Prices

With the corn price representing the demand for anhydrous ammonia and the oil price representing the supply for anhydrous ammonia, a formal regression model was developed using ordinary least squares. This model resulted in the following equation:

$$\textit{Anhydrous ammonia (\$/ton)} = 202 + 43.4 \times \textit{corn (\$/bu)} + 3.18 \times \textit{oil\_9 mo lag (\$/ barrel)} \qquad (1)$$

This regression result has an adjusted R-squared value of 0.85. An R-squared value this high is usually considered a strong fit. Figure 6 shows the actual anhydrous ammonia price versus the predicted anhydrous ammonia price.

Predictions for 2019 and into 2020

During 2018, producers saw fertilizer prices start to rise. Fertilizer prices ended the year higher than they were in 2016 and 2017 but lower than they were in 2013, 2014, and 2015. Given that nitrogen fertilizer prices are dependent upon corn prices and oil prices, this result is unsurprising because oil prices rose considerably during the last half of 2018.

In 2020, producers are likely to see some decreases in fertilizers prices later in the year because oil prices declined some from their fall/winter peaks of 2019. The model to predict anhydrous ammonia prices is based on a nine-month lag in oil prices. Oil prices in late 2018 are at $57 per barrel, and corn futures for 2018 are around $4 per bushel. Keep in mind that the corn price is a forecast too because the model does not lag corn prices. Thus, based on the above model, anhydrous ammonia prices for the fall of 2019 are predicted to be $557 per ton. However, some higher oil prices from 2018 have yet to show up in the model forecast. Oil prices were in the $70 per barrel range from May through October of 2018. Thus, fertilizer prices may not start to decline for a few months yet and may actually increase a little. Other fertilizers are also likely to decrease during the course of 2019 and going into 2020 because there is a strong positive correlation between anhydrous ammonia prices and other fertilizer types (Table 1).

CONCLUSIONS

While these results were for 2019, a similar analysis from a few years earlier yielded a similar result. Going forward, this exact equation may change—but the idea of using the current corn price and the lagging oil price is sound. Economic theory says that an outward shift in the demand curve will lead to higher prices. Higher corn prices will cause a shift to corn acres, which in turn increases the demand for nitrogen. The connection between oil and nitrogen is more complicated but since natural gas and oil are often substitutes, low oil prices usually result in lower natural gas prices. When the natural gas price is low, there is more incentive to use that natural gas to make nitrogen fertilizers—which in turn shifts the supply curve.

Because fertilizer is such an important input to farmers, they would benefit from trying to buy fertilizer at the lowest price point of the year. While the estimated equation may change in the future, the current version should still help farmers find the best time to buy even if the exact price prediction changes.

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Table 1. Correlation of Monthly Fertilizer Prices Since 2010

	Anhydrous	MAP	Urea	DAP	Potash	UAN28	UAN32	10-34-0
Anhydrous	1							
MAP	0.92	1						
Urea	0.89	0.88	1					
DAP	0.89	0.99	0.85	1				
Potash	0.89	0.94	0.91	0.92	1			
UAN28	0.96	0.95	0.95	0.92	0.95	1		
UAN32	0.95	0.94	0.95	0.90	0.93	0.99	1	
10-34-0	0.82	0.86	0.79	0.82	0.81	0.85	0.87	1

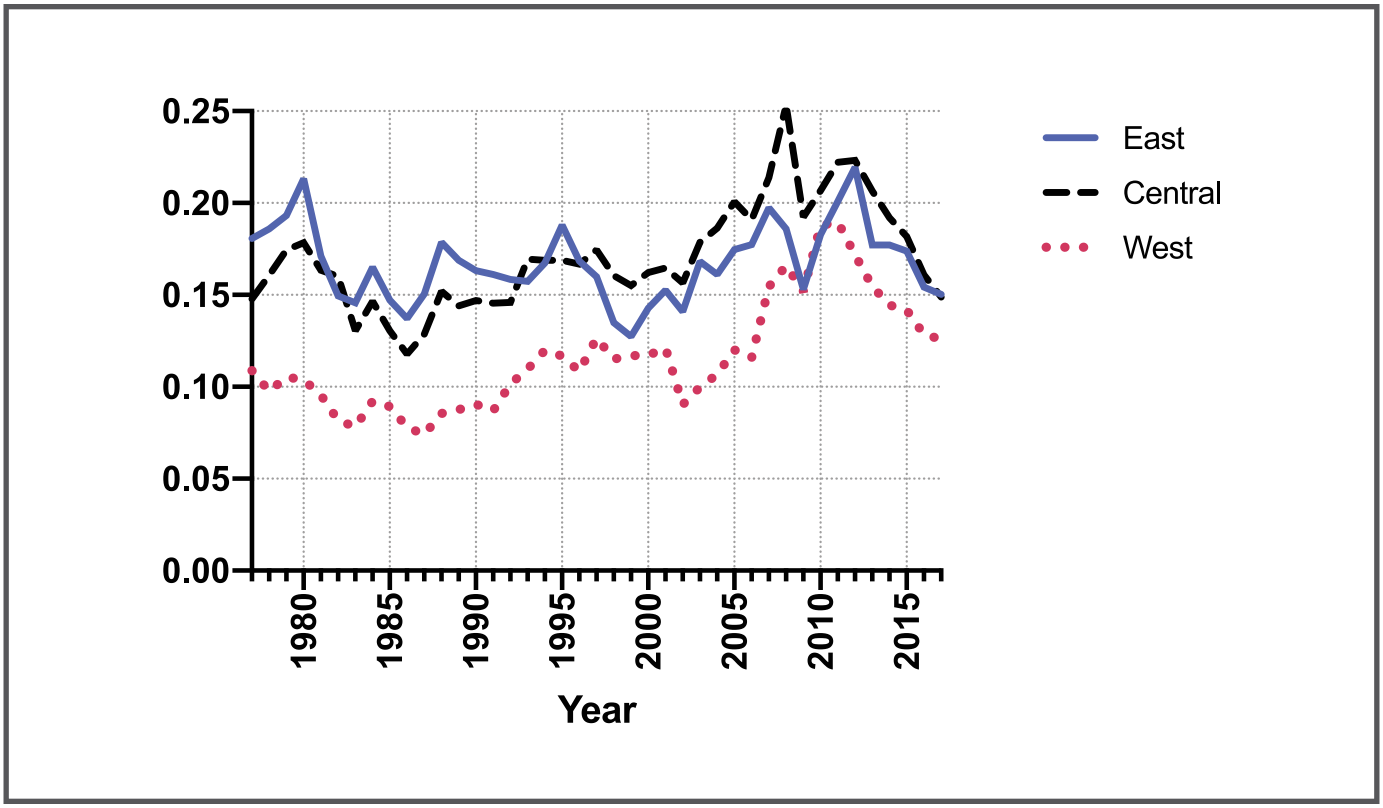

Figure 1. Fertilizer Cost Percentage by Region of Kansas (Source: KFMA data)

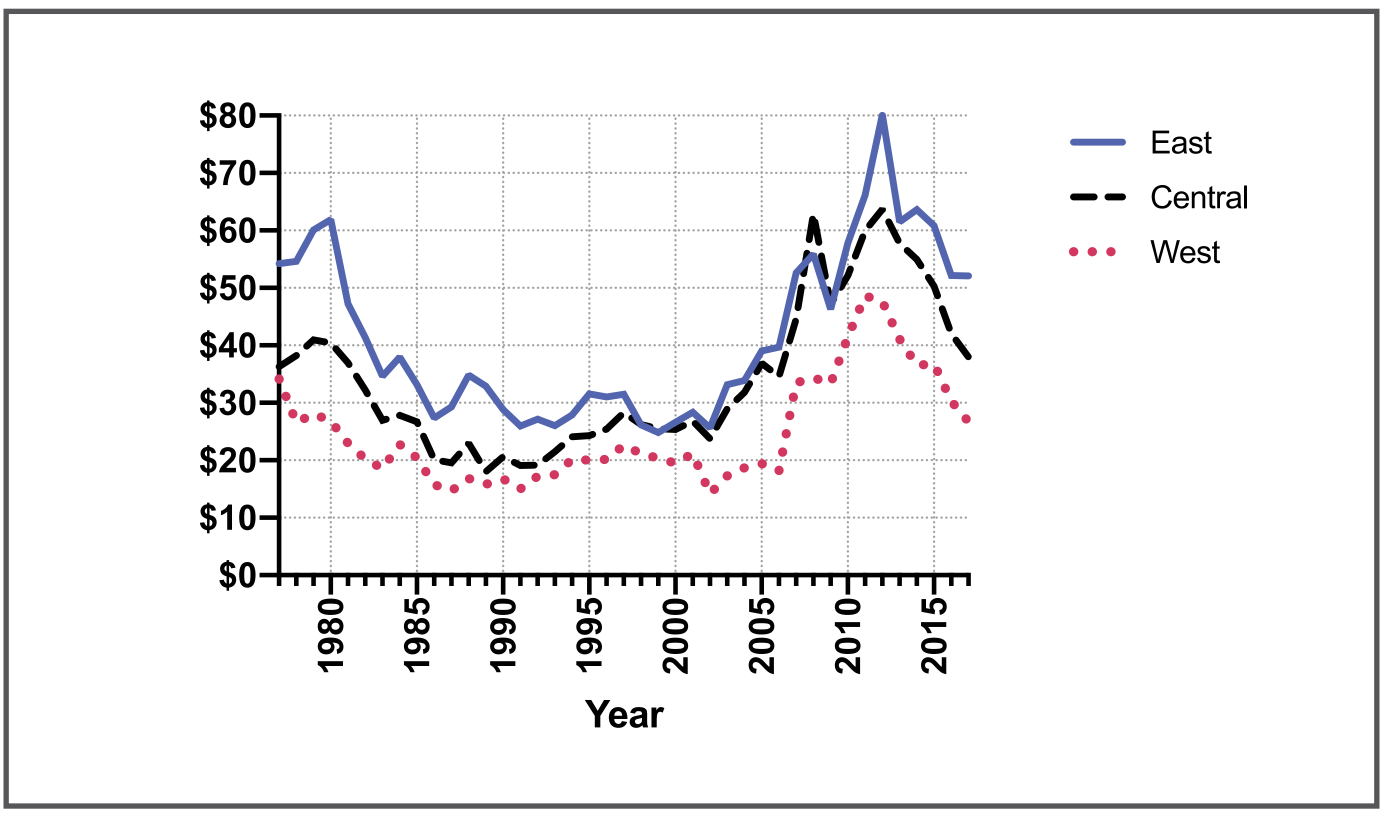

Figure 2. Fertilizer Cost in Real Dollars per Acre by Region of Kansas (Source: KFMA data)

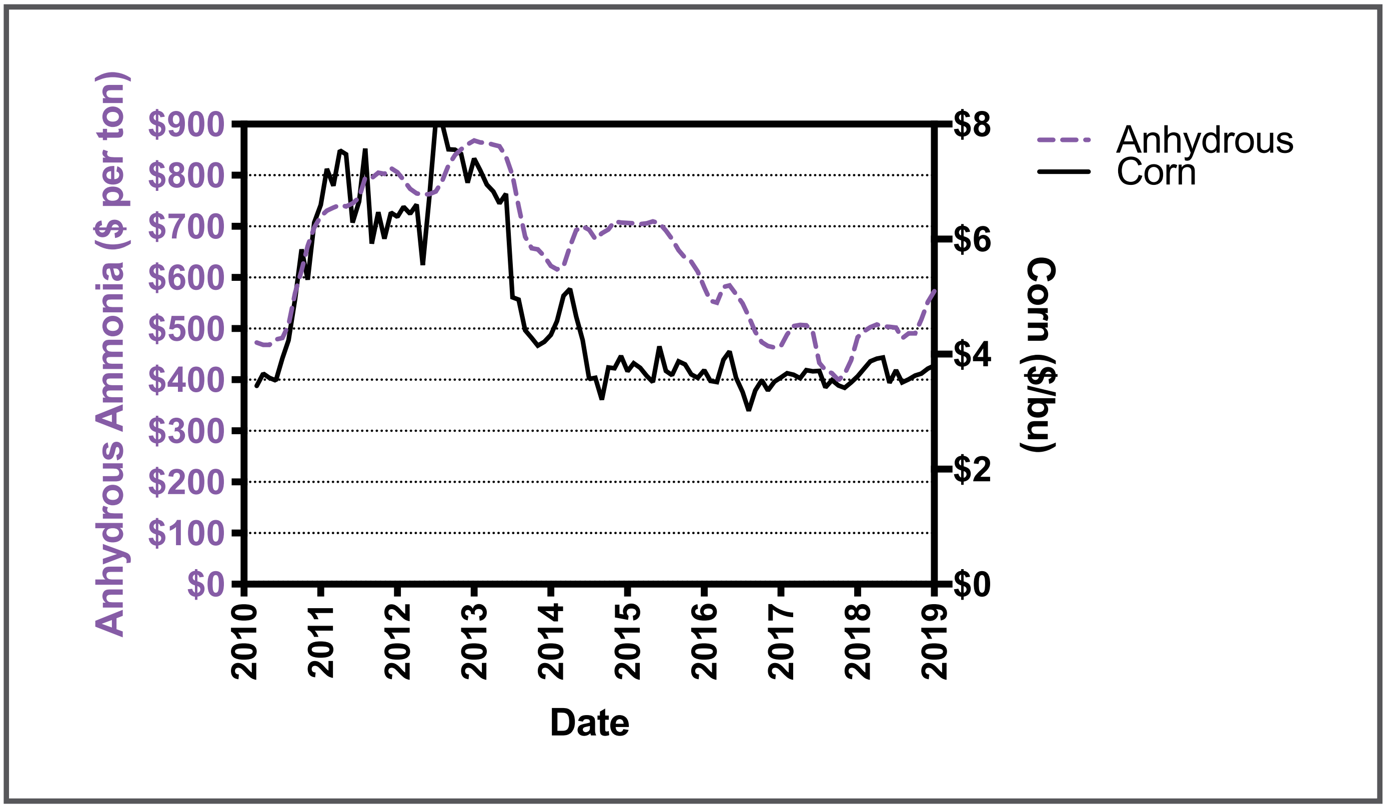

Figure 3. Monthly Anhydrous Ammonia Prices vs. Monthly National Corn Prices

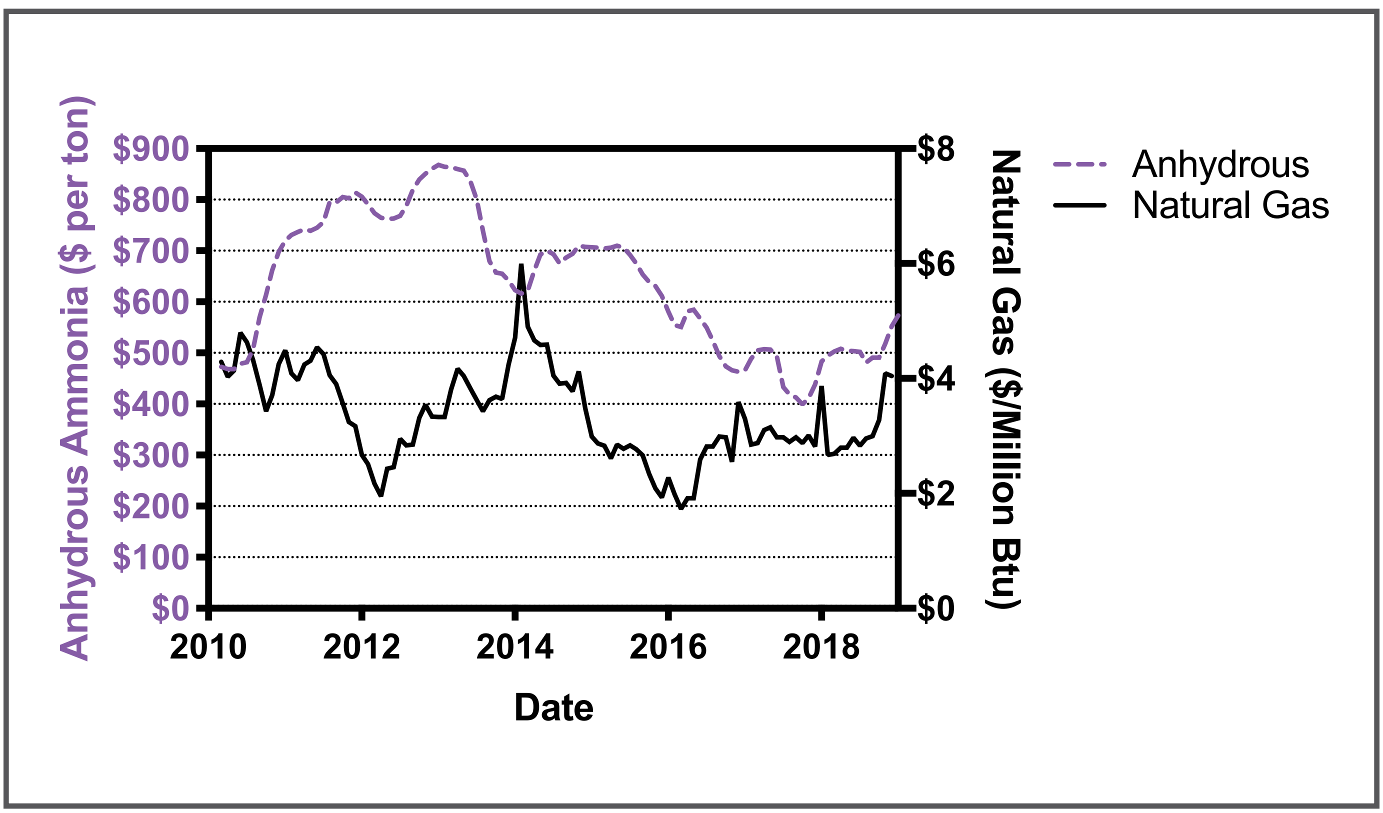

Figure 4. Monthly Anhydrous Ammonia Prices vs. Monthly Natural Gas Prices

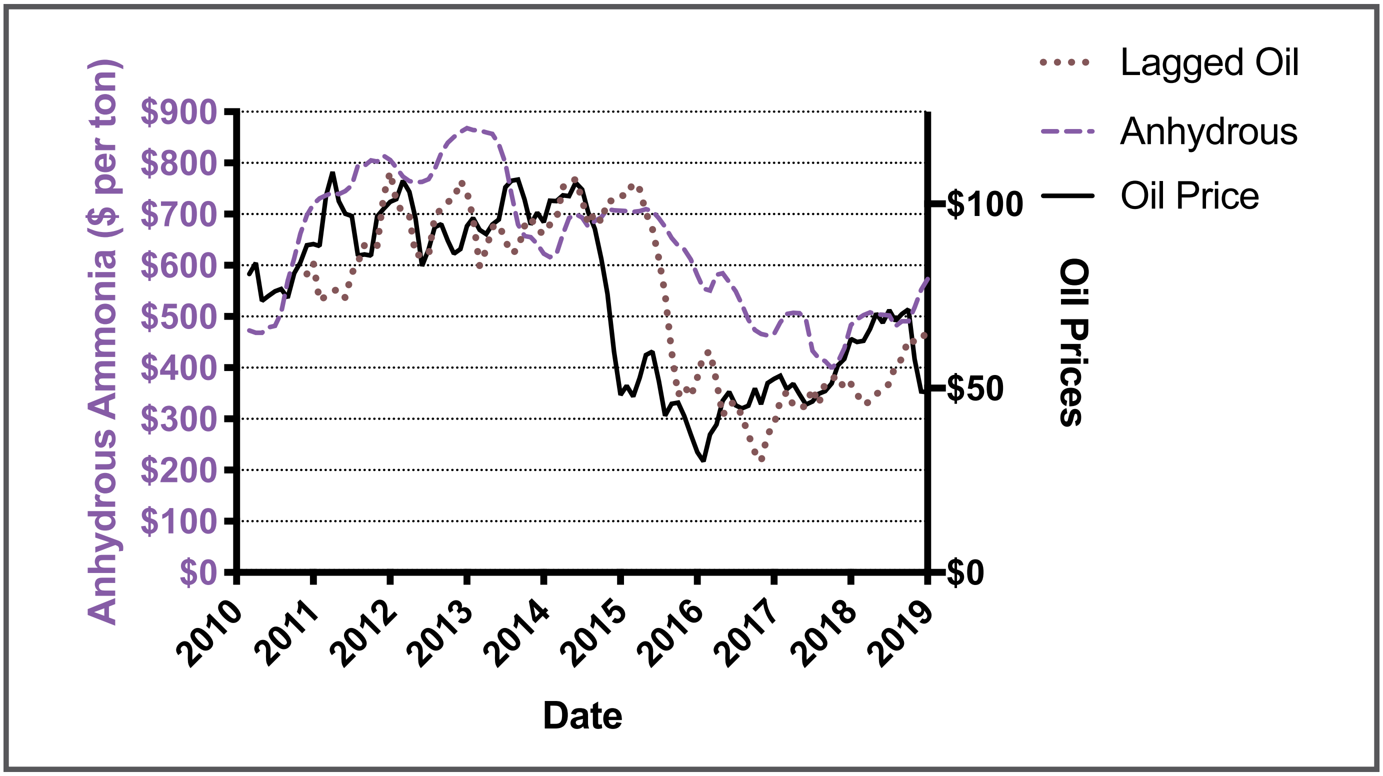

Figure 5. Monthly Anhydrous Ammonia Prices vs. Monthly Oil Prices and Lagged Oil Prices

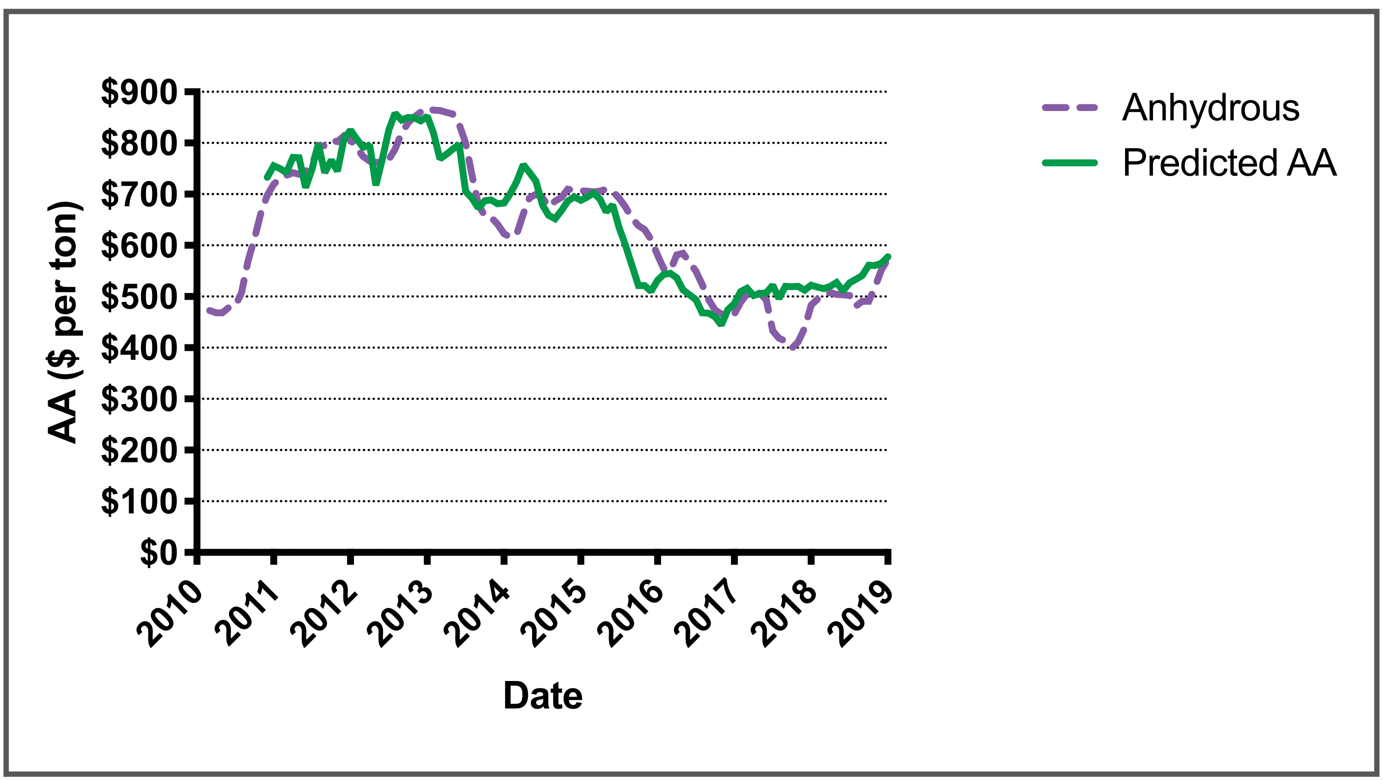

Figure 6. Actual vs. Predicted Anhydrous Ammonia Prices

Economic Feasibility of Sod-Seeded Summer Annuals in Wisconsin Pastures Using Cow-Calf Simulation





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Abstract

This research models three forage systems for cow-calf operations in the Upper Midwest: a common perennial cool-season system (PCS) using alfalfa and cool-season grasses, and two additional forage systems involving perennial Kura clover, with no-till seeded rye in the fall followed by either corn or sudangrass as warm-season forages planted in the spring. The intent is to model the relative profitability using a cow-calf simulation spreadsheet that captures economic repercussions of monthly forage availability derived from experimental grazing trials conducted in Wisconsin. Results indicate that forage systems adding warm-season annuals can provide a peak in forage mass in mid-summer, but lower overall yields did not compensate for increased annual establishment costs when compared to the PCS.

JUSTIFICATION

Uneven distribution of plant growth in perennial cool-season pasture creates challenges for pasture managers attempting to maintain adequate levels of forage mass and nutritive value over the entire grazing season. Reductions in pasture growth rate during mid-summer, characteristic of cool-season species (Cherney and Kallenbach, 2007), can result in reduced animal performance and, potentially, cessation of grazing (Mouriño et al., 2003; Schaefer, Albrecht, and Schaefer, 2014). Climate change predictions such as increased annual temperature; increased spring, fall, and winter precipitation; and lesser, more variable precipitation in summer (Belesky and Malinowski, 2016) threaten to exaggerate the cool-season growth pattern and to exacerbate the "summer slump." However, warmer average temperatures may also lengthen the grazing season, possibly creating an environment for utilization of winter annuals in fall and spring. Given the uneven distribution of forage production as affected by weather and forage species selection, as well as predicted effects from climate change, it may be beneficial for pasture managers to develop complementary forage systems by incorporating species with different growth patterns. Such systems could consist of warm-season species drilled into a PCS (Basweti et al., 2009; Tracy et al., 2010) and sod-seeding winter annuals in the fall for early spring grazing the following year (McCartney, Fraser, and Ohama, 2008; Basweti et al., 2009; Smith et al., 2014).

Warm-season annuals are a promising option for complementary forage systems in the Midwest because they support moderate animal production and can be sod-seeded with a no-till drill into existing legume stands to improve yield without compromising nutritive value. Evaluations of monoculture sudangrass (*Sorghum bicolor* L. Moench), for example, have shown moderate levels of gain in growing animals, ranging from 1.7–2.4 pounds per day (McCuistion et al., 2011). Nieman, Albrecht, and Schaefer (2020) demonstrated cattle gains ranging from 1.5–2.2 pounds per day on sudangrass and corn (*Zea mays* L.) interseeded into Kura clover (*Trifolium abiguum* M. Bieb), when heat stress was not a factor. However, some limitations for adoption of summer and winter annuals are access to a no-till drill, expense of field operations, and nitrogen fertilization (Tracy et al., 2010).

The use of warm-season and winter annual species for complementary forage systems in the Upper Midwest requires careful evaluation. These forages need to provide feed in high quantity and of high nutritive value to achieve animal gain comparable to cool-season perennial species and offset added annual production costs.

The Forage & Cattle Planner (FORCAP) decision support tool can be used to model the interaction between cow-calf herd performance and forage production by matching monthly herd nutrient needs to forage production to estimate annual economic performance of a cow herd with user-specified availability of hay and pasture land (Popp et al., 2014). FORCAP allows the user to manage a host of cattle performance parameters (reproductive performance, timing of calving, cow weight, calf birth weight, weaning weight, etc.) along with pasture management choices (forage species selection, fertility, stocking rate, continuous versus rotational grazing, harvest of excess pasture forage as hay, and selective grazing of hay acreage). The tool has been used to evaluate herd sire genetics (Keeton, Popp, and Smith, 2014), calving season management (Smith et al., 2016), herd size management strategies over time (Tester et al., 2019), and reproductive performance differences using genetic markers (Popp et al., 2020). For this research, FORCAP was adapted for an economic evaluation of cow-calf management practices common in Wisconsin, with the objective to assess whether the added costs of incorporating warm-season and winter annuals are offset by added and timely forage production for cow-calf operations in Wisconsin.

MODEL DATA BACKGROUND

Forage Data

The data entered into FORCAP for the PCS was based an average yield, growth rates, and nutritive value of three different grasses (meadow fescue [*Schedonorus pratensis* (Huds.) P. Beauv], tall fescue [*Schedonorus arundinaceus* (Schreb.) Dumort], and orchardgrass [*Dactylis glomerata* L.]) grown in binary mixture with alfalfa (*Medicago sativa* L.) derived from Nieman, Albrecht, and Schaefer (2019). Each binary mixture was replicated three times. Because nutritive value and forage yield differences were minimal among the three binary mixtures, data from all mixtures was averaged for use in the simulation of the PCS. Pastures were strip-grazed from May to October in 2015 and 2016.

Forage production and nutritive value data for sudangrass and corn sod-seeded on June 1 into chemically suppressed Kura clover was collected at the same site from 2014–2016 (Nieman, Albrecht, and Schaefer, 2020). Three replicates each were dedicated to the two annual combinations. Both summer annual mixtures were followed by rye interseeded into Kura clover in fall, for spring grazing in 2015 and 2016. Sudangrass-Kura clover (SG-KC) was strip-grazed from mid-July to mid-September, using two 24-day rotations, and corn-Kura clover (C-KC) was strip-grazed from mid-July to mid-August for 24 days using only one rotation. Winter rye was planted in late September of 2014 and 2015 in SG-KC and C-KC and grazed for 24 and 31 days in spring of 2015 and 2016, respectively. Detailed pasture management methods were described in Nieman, Albrecht, and Schaefer (2020).

For all species and replicates, pre-grazing forage mass was measured weekly and analyzed for crude protein (CP), neutral detergent fiber (NDF), in vitro true digestibility (IVTD), and neutral detergent fiber digestibility (NDFD). Total digestible nutrient (TDN) concentrations were calculated from nutritional analyses (CP, NDF, IVTD, NDFD) using a recent equation (NASEM, 2016). Post-grazing forage mass samples were taken to determine the amount of forage harvested by cattle. Total forage harvested was calculated from weekly pre- and post-grazing samples; the difference was divided by the days between pre- and post-harvest to determine forage harvested per day and then multiplied by 7 days to determine total forage harvested per week for each replicate. Weeks were summed to determine total forage harvested per month for simulation in FORCAP to assess forage harvested by forage species and total system.

Adjustments to FORCAP

Many grazing trials are conducted using stocker cattle to evaluate forage production, nutritive value, and animal rate of gain because of the relative ease of stocker cattle management and interpretation of results compared to cow-calf trials. Evaluating pasture forage systems for cow-calf operations is much more complex since year-round feeding is required and producers usually guard against uncertain pasture carrying capacity by having excess pasture or feeding hay. Nonetheless, cow-calf operations are much more prevalent in Wisconsin than stocker cattle operations; therefore, this evaluation utilized forage data collected in a stocker grazing trial to simulate a complementary forage system for a cow-calf operation.

Since FORCAP was created for Arkansas application, adjustments were made to make its simulations relevant to the Upper Midwest. Therefore, the adjusted FORCAP was termed FORCAP North. The Livestock Marketing Information Center (http://www.lmic.info) tracks long-term monthly price histories for medium- and large-frame one feeder cattle in 100-pound increments for South Dakota and Iowa. The simple average of those two state price series was chosen as representative of Wisconsin because historical price information for Wisconsin, a dairy state, was not available for the past 15 years since they no longer track historical prices for beef cattle. Further, Illinois market price data lacks sufficient volume to report monthly prices on a consistent basis. For the same reasons, monthly cull cow and bull prices were those reported for Sioux Falls, South Dakota, for 75% to 80% lean 1,200- to 1,500-pound commercial cows and grade 1 and 2 1,500- to 2,000-pound slaughter bulls, respectively. To remove the effect of cyclically high or low prices, 10-year averages of monthly prices were deflated to 2016 prices using national beef cattle prices (NASS, 2018a) for the respective category of cattle. Feeder steer and heifer prices were linearly interpolated across 100-pound weight categories to reflect the historical price slide for weaned calves.

The following average weights were used in the FORCAP "Cattle" tab: cull cow weight of 1,400 pounds, 1,100-pound cows at first calving, 80-pound birth weight, 580-pound steers and 540-pound heifers as weaned calves sold at 7 months of age, and 2,000-pound slaughter bull weight. Calving month ranged from March to June, with a modal calving month of April and an average number of eight calves over the life of a cow. Breeding failure rate was set to 7.5%. Cow and calf mortality were set to 1% and 3%, respectively. Given these performance statistics, a breeding herd of 150 cows required annual retention of 21 heifer calves to replace 19 cull cows after adjusting for death losses. Weaned steer and heifer calves sold amounted to 67 and 46 head annually.

Selected Options for FORCAP North

Actual total forage harvested and forage harvested per month data from Nieman, Albrecht, and Schaefer (2019; 2020) was used, along with the previously mentioned forage species choices into FORCAP North (Table 1). These values represent forage actually consumed by grazing steers and were translated to needed model estimates of forage production potential (measured as harvestable forage 2 inches above ground) by using 60% grazing and haying efficiency as observed in the above study and a default value in FORCAP. Furthermore, forage species composition by area was simulated for SG-KC and C-KC by modeling a complementary system with 50% of land dedicated to PCS and 50% of land dedicated to the pastures sod-seeded with rye and sudangrass or corn, respectively.

FORCAP cow numbers were adjusted to represent a large Wisconsin cow-calf herd (Table 2). The simulated forage systems had 200 acres in pasture and 50 acres in hay, with the aforementioned 150-cow breeding herd serviced by six herd sires. For all systems, hay pastures were composed of 20% orchardgrass, 75% alfalfa, and 5% bromegrass (*Bromus inermis* L.); hence, economic simulation of hay production could be excluded from the analysis because all forage systems had the same performance on hayland. Forage requirements by month were based on the dry matter intake needs by cattle category and were based on body weight and adjusted for monthly gestational changes in nutritional needs. In months when total digestible nutrient intake was insufficient to maintain cow body condition, supplemental corn and hay were fed to cows, replacement heifers, and bulls as needed. Crude protein intake needs are also tracked in FORCAP but were found to be non-limiting.

All forage systems were given the FORCAP option to graze hayland in October. Hayland was not grazed at any other time. In addition to hay production on hayland, hay bales were produced on pasture when forage was determined to be in excess based on animal number and nutritional requirements. Farmland, cattle numbers, and capital costs remained constant for the comparison across the three forage systems; the only differences in the comparison were forage parameters—production, nutritional value, growth rate, and pasture establishment costs. Hence partial cash returns, after specified direct costs, were calculated as the sale of cattle and excess hay, less costs for forage maintenance, feed, supplements, seed, fuel, twine, and operating interest. Hay sales and production costs varied with the production system. Note that partial cash returns are useful for making relative profitability comparisons across systems but do not reflect profitability of an entire system. The reader is thus advised to treat partial cash return with caution since opportunity cost of land and labor used, as well as ownership charges for cattle and equipment, were purposely excluded to assess changes in relative profitability only.

Pasture Establishment Costs

Pasture establishment costs were determined based on 2017 seed and herbicide prices. All costs for custom operations were the statewide average derived from the Wisconsin Custom Rate Guide 2017 (NASS, 2018b). Perennial establishment (PCS and Kura clover) costs included custom rates for pre-plant tillage, glyphosate herbicide application, and no-till planting (Table 3) and were prorated over expected stand lives. Costs for SG-KC and C-KC included the Kura clover establishment, with additional costs for annual seed and herbicide (paraquat dichloride) applied to suppress Kura clover prior to sudangrass and corn sod-seeding. Forage clipping of corn stalks and sudangrass stems was necessary in September prior to planting of the winter rye. Custom no-till planting operations were budgeted for all annual species.

Economic Analyses

The PCS had several advantages over SG-KC and C-KC. A longer fall growing season in PCS (Figure 1) resulted in 0 days of supplemental hay feeding in October, compared to 12 and 19 days for complementary systems, SG-KC and C-KC, respectively. For the calendar year, supplemental feed was fed for 181, 193, and 200 days in PCS, SG-KC, and C-KC, respectively (Table 2). Each system produced forage in excess of dry matter intake needs of the grazing herd for part of the growing season. Surplus forage harvested from pasture was highest for PCS with 733 1,200-pound bales compared to 440 and 395 bales for SG-KC and C-KC, respectively. Overall, this resulted in excess hay sales for PCS in the amount of $3,274, whereas supplemental hay purchases of $16,849 and $22,072 were needed for SG-KC and C-KC, respectively (Table 4). Supplemental corn was estimated to be required for cows and replacement heifers from December through April in the amount of 49,399 pounds or $4,332 in PCS, whereas 63,361 and 62,688 pounds or $5,556 and $5,497 per year were required for SG-KC and C-KC from November to April, respectively. Annual total forage establishment cost as specified in Table 3 was much greater for complementary systems averaging $104.44 per acre for SG-KC and $131.24 per acre for C-KC, whereas PCS was $33.03 per acre. Greater production costs and lower forage production resulted in partial cash returns that were $36,145 and $46,905 lower than PCS for the SG-KC and C-KC forage systems, respectively (Table 4).

Improvements and Implications

Warm-season and winter annual species have been proposed to help forage-based livestock producers manage variable precipitation and warmer summers, as well as longer growing seasons associated with climate change. We simulated the implementation of warm-season annual species in a pasture forage production system by allocating half of the pasture acreage to a system that involved sod-seeding sudangrass or corn and winter rye into a stand of Kura clover. The other half of the pasture acreage was assumed to be alfalfa-grass pasture. All systems were then compared. Based on forage production in 2015 and 2016, there was no economic benefit associated with the forage systems that involved sudangrass or corn when compared to the cool-season perennial pasture.

While warm-season annual grasses have greater yield potential in a growing season than perennial cool-season forage crops (Loomis and Williams, 1963; Helsel and Wedin, 1981), the warm-season species in this study did not have greater yields than PCS. Potential explanations are the competition with Kura clover and nitrogen deficiency. Kura clover was used in this study because Wisconsin pastures are often relegated to marginal landscapes that are prone to erosion if tilled. Previous research has demonstrated that corn can be interseeded with a no-till drill into established Kura clover for silage or grain production (Zemenchik et al., 2000; Affeldt et al., 2004) with little or no nitrogen fertilizer and with minimal risk of soil erosion (Siller, Albrecht, and Jokela, 2016). Similarly, Affeldt (2003) demonstrated that sudangrass could be no-till drilled into established Kura clover, also for mechanical harvest. These mixtures had not previously been evaluated under grazing. In this study, fertilizer was not applied to SG-KC or C-KC. This decision was based on results from previous research and with the expectation that grazing cattle would cycle sufficient nitrogen onto the pasture through urine and manure and treading would damage clover, resulting in above and below ground tissue death and nitrogen mineralization. However, it was visually noted that corn and sudangrass plants showed signs of nitrogen deficiency, indicating that yields may have been improved with nitrogen application, though at added cost. Additionally, environmental conditions were favorable in 2015 and 2016 and were without any prolonged drought. Hence, the question remains if warm-season annuals can mitigate a drought situation. With variable precipitation and a drought not guaranteed, there is a risk to incorporating warm-season annuals, since during non-drought summers the increased costs of establishment and lower yields would reduce profits. On the other hand, during a drought summer, warm-season annuals may be beneficial. If one simulates a drought in FORCAP by reducing production of PCS forages by 45% for the months of July and August, annual forage production is reduced by 18%. This 18% reduction would be sufficient to cause the SG-KC system to be more productive as long as the SG-KC system did not suffer a yield penalty under those drought conditions.

For complementary systems to be more profitable in the Upper Midwest, the growing season for annuals may need to be longer than allowed in this study. Additional forage yield would help to compensate for establishment costs. Each year, SG-KC pastures were clipped to prepare for rye planting in late September. Delaying such clipping to allow a third grazing rotation would add yield potential, albeit at the cost of delayed rye planting. Additionally, in C-KC, grazing ended by mid-August. For that system, oats (*Avena sativa* L.) may be an option for fall grazing if planted no later than mid-August. Oats sown in monoculture in early August accumulated greater than 6,000 pounds per acre of high nutritive value forage before killing frost at two locations in southern Wisconsin (Contreras-Govea and Albrecht, 2006). Further, for C-KC, this study constrained corn grazing to 24 days, although another option for producers would be to adjust stocking rate to allow for longer grazing into the fall. Sod-seeded winter rye in this study did not provide any earlier season grazing compared to cool-season grass species. This may have occurred because rye was sod-seeded, which delays spring forage production compared to winter annuals on a clean seed-bed (Utley, Marchant, and McCormick, 1976). Though not examined in this study, winter rye may also be suitable for fall grazing in the Upper Midwest. Finally, an attempt to remove the winter annual from the complementary forage systems to save cost would likely fail. A grass is necessary if producers want to graze this system in the spring, in order to prevent bloat likely to occur with pure Kura clover.

Although incorporation of warm-season or winter annuals as complementary forages in cool-season perennial pasture systems in the Upper Midwest may become necessary and more economically appealing through the progression of climate change, this practice did not prove to be economically advantageous in the grazing seasons 2015 and 2016 when compared to alfalfa-grass pasture. Additional years of observation under variable and adverse weather conditions at more locations would provide greater insight into successfully filling forage production gaps. However, utilizing forage species with complementary growth patterns has great potential, and testing of several forage species combinations may be required to discover a profitable system. Researchers should continue to develop forage systems in the Upper Midwest that provide forage-based livestock producers with economical and sustainable solutions to potential "summer slumps" and a changing climate.

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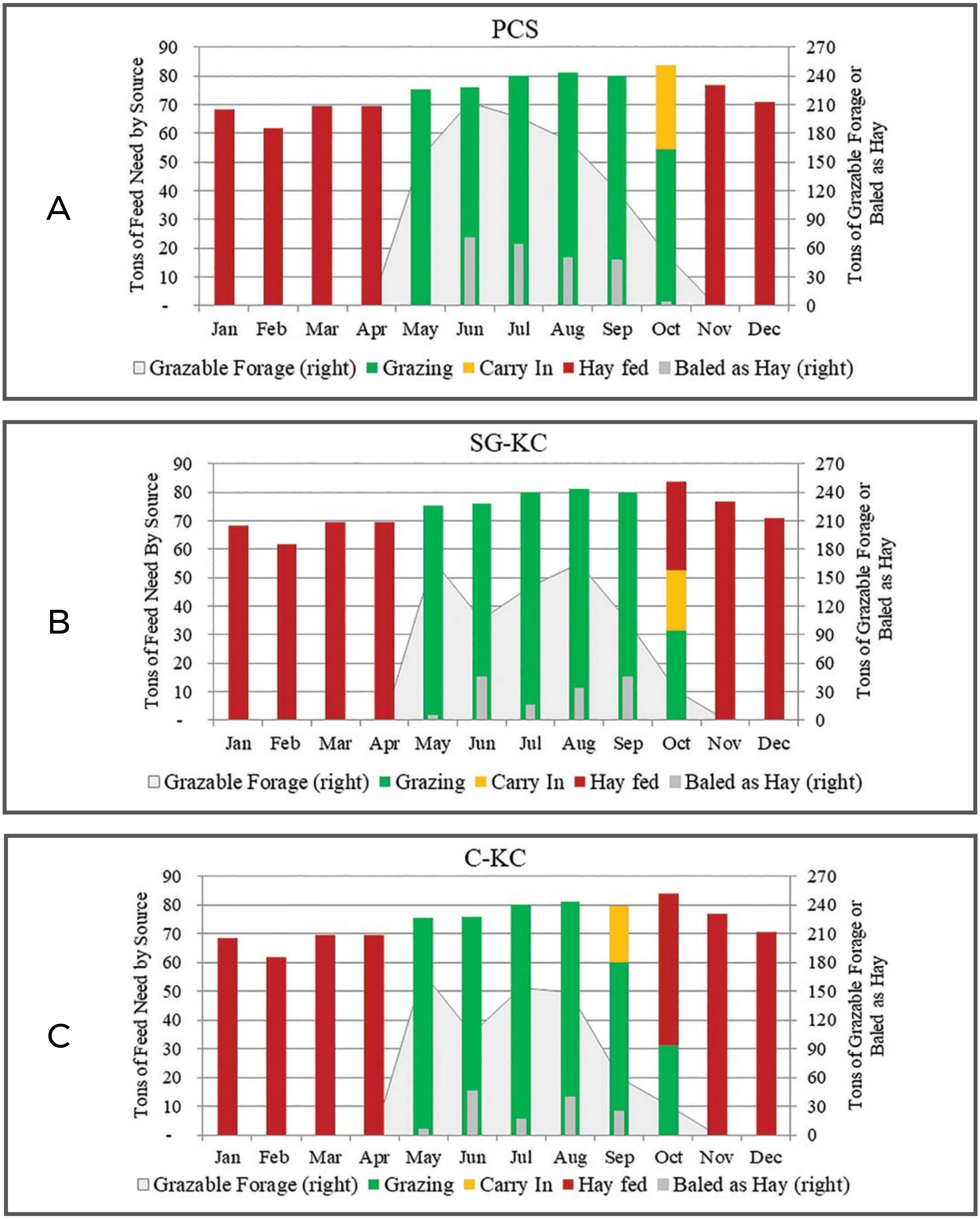

Figure 1. Comparison of Forage Balance in Three Forage Systems. *A*, Perennial cool-season (PCS). *B*, Complementary system with summer planted sudangrass and fall planted rye sod-seeded into Kura clover (SG-KC). *C*, Complementary system with summer planted corn and fall planted rye sod-seeded into Kura clover (C-KC).

Table 1. Forage Production and Quality Parameters Used as Input for FORCAP for Each Forage Species Mix as Averaged over 2015 and 2016 from Wisconsin Grazing Trials

	PCS[a]			SG-KC[b]			C-KC[c]		
Month	**Production[d] lbs/acre**	**CP %**	**TDN %**	**Production lbs/acre**	**CP %**	**TDN %**	**Production lbs/acre**	**CP%**	**TDN %**
May	2,530	22	65	2,800	18	58	2,800	18	58
June	3,460	18	58	NA[e]	NA	NA	NA	NA	NA
July	3,210	19	57	1,330	13	55	1,690	15	55
Aug	2,810	22	60	2,450	13	52	1,920	10	52
Sept	1,960	25	62	1,350	14	65	NA	NA	NA
Oct	750	26	63	NA	NA	NA	NA	NA	NA
Total	**14,720**			**7,930**			**6,410**		

[a]Perennial cool-season system (PCS) consisting of alfalfa-grass mixtures.

[b]Forage availability is reported for 100% of fall planted rye and spring planted sudangrass sod-seeded into Kura clover (SG-KC) to allow comparison to PCS and C-KC. Note that gaps in forage grazing[e] in June and October are filled since 50% of PCS production is available for grazing in the SG-KC system (Figure 1). SG-KC production is the simple average of PCS and SG-KC.

[c]Forage availability is reported for 100% of fall planted rye and spring planted corn sod-seeded into Kura clover (C-KC) to allow comparison to PCS and SG-KC. Note that gaps in forage grazing[e] in June, September, and October are filled since 50% of PCS production is available for grazing in the C-KC system (Figure 1). C-KC production is the simple average of PCS and C-KC.

[d]Production represents observed forage harvested in grazing trials divided by 60% grazing efficiency to determine total forage biomass available above ground. Using forage production rather than forage harvested allows the user to enter different grazing efficiency if desired in FORCAP. Similar performance as observed with steers is assumed for cow-calf pairs in this modeling effort.

[e]While pasture forages are growing, they are not modeled as available here since grazing trials had distinct grazing periods.

Table 2. Monthly Forage Required by a 150-Cow Herd vs. Source of Nutrition with Deficits Met by Feeding Supplemental Hay and Corn[a] and Excess Baled as Hay as Simulated Using FORCAP

	Forage DM (Tons) Needed by Cattle Type						Forage DM Grazed Including Carry-In from Prior Month (Tons)			Days on Feed Using Supplemental Hay			Pounds of Corn Fed			Excess Forage (Bales)[b]		
Month	**Cows**	**Bulls**	**Repl.[c] Heifers**	**Heifer Calv.[d]**	**Steer Calv.[d]**	**Total**	**PCS[e]**	**SG-KC[f]**	**C-KC[g]**	**PCS**	**SG-KC**	**C-KC**	**PCS**	**SG-KC**	**C-KC**	**PCS**	**SG-KC**	**C-KC**
Jan	58.6	2.9	4.6	1.1	1.2	68.3	-	-	-	31	31	31	10,404	12,712	12,615	-	-	-
Feb	54.3	2.6	4.9	-	-	61.8	-	-	-	28	28	28	11,709	13,883	13,791	-	-	-
Mar	60.8	2.9	5.8	-	-	69.5	-	-	-	31	31	31	9,709	12,128	12,026	-	-	-
Apr	61.9	2.8	4.8	-	-	69.4	-	-	-	30	30	30	7,375	9,813	9,710	-	-	-
May	70.6	2.9	1.9	-	-	75.4	75.4	75.4	75.4	-	-	-	-	-	-	-	-	-
Jun	72.5	2.8	0.6	-	-	75.9	75.9	75.9	75.9	-	-	-	-	-	-	224	143	143
Jul	76.3	2.9	-	0.4	0.4	80.0	80.0	80.0	80.0	-	-	-	-	-	-	201	50	50
Aug	74.3	2.9	-	1.9	2.0	81.0	81.0	81.0	81.0	-	-	-	-	-	-	157	104	125
Sep	68.8	2.8	-	4.0	4.2	79.8	79.8	79.8	79.8	-	-	-	-	-	-	151	143	77
Oct	66.3	2.9	-	7.1	7.4	83.8	83.8	52.5	31.4	-	12	19	-	-	-	-	-	-
Nov	58.2	2.8	0.9	7.2	7.7	76.8	-	-	-	30	30	30	-	392	301	-	-	-
Dec	58.4	2.9	3.3	3.0	3.1	70.7	-	-	-	31	31	31	3,287	5,562	5,468	-	-	-

[a]Forage requirements by month were based on the dry matter intake needs by cattle category and body weight. In months where total digestible nutrient intake was insufficient to maintain cow body condition, supplemental corn and hay were fed to cows, replacement heifers, and bulls as needed. Crude protein intake was also tracked in FORCAP but found to be non-limiting.

[b]Excess forage was baled when forage mass available was sufficient to bale at least half of a 1200-lb bale per acre.

[c]Replacement heifers required to maintain herd size after cull cows are sold.

[d]Heifer and steer calves begin grazing at 4 months of age, thereby reducing cow nutrition needs. Last of calves are sold in January at 7 months of age given calving distribution.

[e]Perennial cool-season system (PCS) grazing system performance (Table 1).

[f]Perennial cool-season on half of pasture land along with rye and sudangrass sod-seeded into Kura clover (SG-KC) on the other half of the pasture (Table 1).

[g]Perennial cool-season on half of pasture land along with rye and corn sod-seeded into Kura clover (C-KC) on the other half of the pasture (Table 1).

Table 3. Costs to Establish Three Forage Systems, Wisconsin 2017			
	PCS[a]	SG-KC[b]	C-KC[c]
Perennial Establishment		**$/acre**	
Herbicide	3.12	3.12	3.12
Herbicide Application	8.00	8.00	8.00
Tillage	14.00	14.00	14.00
Planting (no-till)	19.00	19.00	19.00
Seed	88.01	96.00	96.00
Prorated Total	**33.03[d]**	**7.01[e]**	**7.01[e]**
Warm-Season Annual Establishment			
Herbicide	0.00	0.94	0.94
Herbicide Application	0.00	8.00	8.00
Planting (no-till)	0.00	19.10	20.20
Seed	0.00	52.50	105.00
Summer Annual Total	**0.00**	**80.54**	**134.14**
Rye Establishment Costs			
Clipping	0.00	14.20	14.20
Planting (no-till)	0.00	19.10	19.10
Seed	0.00	55.00	55.00
Fall Annual Total	**0.00**	**88.30**	**88.30**
Total	**33.03**	**175.85**	**229.45**
System Total[f]	**33.03**	**104.44**	**131.24**

[a]Perennial cool-season system (PCS) consisting of alfalfa-grass mixtures.

[b]System with half the pasture land devoted to PCS and the other half in rye and sudangrass sod-seeded into Kura clover (SG-KC).

[c]System with half the pasture land devoted to PCS and the other half in rye and corn sod-seeded into Kura clover (C-KC).

[d]Perennial establishment over 4 years.

[e]Perennial establishment over 20 years.

[f]PCS costs are incurred on 200 acres; SG-KC and C-KC costs are the weighted average of PCS and SG-KC or C-KC totals with 100 acres in PCS and 100 acres in SG-KC or C-KC, respectively.

Table 4. Estimated Gross Receipts and Direct Costs for Three Forage Systems Using Simulated Forage Production for a 150-Cow Herd Based on Results from Wisconsin Growing Seasons in 2015 and 2016

Forage System	PCS[a]		SG-KC[b]		C-KC[c]	
	Gross Receipts (% of Total Receipts)					
Steer Calves	$65,854	(51.7)	$65,854	(53.0)	$65,854	(53.0)
Heifer Calves	$39,076	(30.7)	$39,076	(31.5)	$39,076	(31.5)
Cull Cows	$16,966	(13.3)	$16,966	(13.7)	$16,966	(13.7)
Cull Herd Sire	$2,263	(1.8)	$2,263	(1.8)	$2,263	(1.8)
Excess Hay	$3,274	(2.6)	$0	(0.0)	$0	(0.0)
Total Receipts	**$127,433**	**(100)**	**$124,159**	**(100)**	**$124,159**	**(100)**
	Direct Cost (% of Total Receipts)					
Forage Maintenance[d]	$6,607	(5.2)	$20,888	(16.8)	$26,248	(21.1)
Purchased Hay	$0	(0.0)	$16,849	(13.6)	$22,072	(17.8)
Corn	$4,332	(3.4)	$5,556	(4.5)	$5,497	(4.4)
Fuel	$2,059	(1.6)	$2,106	(1.7)	$2,138	(1.7)
Twine	$1,012	(0.8)	$719	(0.6)	$674	(0.5)
Specified Direct Costs	$14,010	(11.0)	$46,118	(37.1)	$56,628	(45.6)
Operating Interest[e]	$333	(0.3)	$1,095	(0.9)	$1,345	(1.1)
Partial Cash Returns after SDC	**$113,091**	**(88.7)**	**$76,946**	**(62.0)**	**$66,186**	**(53.3)**

[a]Perennial cool-season system (PCS) consisting of alfalfa-grass mixtures.

[b]System with half the pasture land devoted to PCS and the other half in rye and sudangrass sod-seeded into Kura clover (SG-KC).

[c]System with half the pasture land devoted to PCS and the other half in rye and corn sod-seeded into Kura clover (C-KC).

[d]Forage maintenance costs were spread over 4 years for alfalfa grass and 20 years for Kura clover (Table 3).

[e]Operating interest is calculated over a 6-month period using a 4.75% annual operating loan interest rate with specified direct costs.

Submission Guidelines

PURPOSE OF THE JOURNAL

The Journal is published by the American Society of Farm Managers and Rural Appraisers. The Society decided in 2003 to move from hard copy format to online publication, although you may obtain a hard copy from the American Society headquarters for the cost of reproduction.

The *Journal of the American Society of Farm Managers and Rural Appraisers* is a refereed journal. Articles submitted for publication undergo a peer review process before being accepted for publication. The peer review process is designed to ensure that articles meet certain standards and that the Journal is a publication of high standing.

The Journal seeks articles from those working in all the fields of farm management, rural appraisal, and agricultural consulting. Therefore it is not just for academics, but is also open to contributions from all those involved in rural property valuation and/or management and consulting endeavors.

The purpose of the Journal is to provide a forum for those in the farm management, rural appraisal, and agricultural consulting fields to share experiences with others, from which we can all learn.

OBJECTIVES

The objectives of the Journal are to:

1. Present papers relevant to farm managers, rural appraisers, farm advisors, consultants, academics, students, and all others interested in farm management, rural appraisal, and agriculture in its widest sense.

2. Report new challenges and pressures that are developing, for the use of agricultural and rural resources.

3. Encourage practical and problem solving contributions highlighting common farm management, rural appraisal, and agricultural consulting issues and principles.

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4. Manuscript Title. Manuscript titles should not exceed 10 words, should encompass the topic of the paper, and should be designed to attract potential readers.

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a. Manuscripts should not exceed approximately 5,000 words and must be submitted electronically.

b. Use left justification only.

c. Double-space all material throughout the manuscript, including abstract, acknowledgments, footnotes, and references.

d. Use 12-point Times New Roman font style throughout.

e. Allow 1" margins on all sides. Do not use right-justified margins (i.e., use jagged right margins).

f. Do not use the end-of-line hyphenation feature.

g. All pages and lines must be numbered. Line numbers are to run consecutively throughout the entire manuscript from page one to the end of the manuscript; **do not** re-start numbers on each page.

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10. Photos. Photos and graphics must be sent as separate files. Resolution should be 300 dpi. Preferred format is JPEG; TIFF and PDF image files also accepted.

11. Math/Equations. *Use only essential mathematical notation.* Consecutively number equations throughout the text. When displaying equations, place equation number within parentheses at flush-right margin; center the equation. Use italic typeface for all variables, both within equations and within narrative.

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c. Unsuitable articles are returned to the authors with a short note of explanation from the Editor. *Failure to adhere to the Manuscript Format Guidelines will be cause for the manuscript to be returned to the authors.*

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e. Following review, authors may be asked to resubmit their article in revised form.

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15. Submissions. Electronic submission of manuscripts is required and must include the lead author's e-mail address. The manuscript must be formatted per above guidelines as a Word attachment to the ASFMRA, Attn: Alex Clark.

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