IMPACTS OF CROP INSURANCE ON CASH RENTS

BY

BLAINE S. NELSON

THESIS

Submitted in partial fulfillment of the requirements
for the degree of Master of Science in Agricultural and Applied Economics
in the Graduate College of the
University of Illinois at Urbana-Champaign, 2017

Urbana, Illinois

Master’s Committee:

Professor Bruce Sherrick, Chair
Clinical Assistant Professor Todd Kuethe
Associate Professor Nick Paulson
Associate Professor Katherine Baylis

ABSTRACT

This study examines the degree to which net payments from federal crop insurance products impact cash rents paid for farmland. A spatial panel model is employed to control for spatial dependence and heterogeneity in cash rental rates. Results show that producers factor a statistically significant proportion of the value received from crop insurance into cash rents. However, the directly measurable rate is lower than found in previous studies. This result likely reflects the complexity in the relationship between losses and crop insurance rates, and the aggregation across producers in both measured rent and estimates of the net value of crop insurance to a producer. Further, the indirect effects of crop insurance and the ancillary impacts of a producer's risk profile are difficult to identify independently due to the highly variable nature of crop insurance payments, and the smoothed nature of cash rental values. Nonetheless, even as the model removes much of the variation in the data, this analysis shows crop insurance is an important factor in a producer's expected revenue, as cash rents are positively affected in counties that receive consistent and positive net value.

TABLE OF CONTENTS

CHAPTER 1 - INTRODUCTION

1.1 - Purpose and Contribution

Low interest rates coupled with large commodity price increases resulted in record high agricultural land values around 2014 before receding slightly over the past two years. Cash rents and crop insurance subsidies closely tracked the increase and decline in land values, growing to record levels in 2014 before decreasing through 2016. The growth in Federal crop insurance, specifically the growth in premium subsidies, has exposed federal crop insurance to increased public scrutiny. For this reason, understanding the impacts of crop insurance on cash rents is vital as the program and producers move forward. This thesis seeks to quantify the impacts of crop insurance on cash rents.

The discussion of farmland values in literature is extensive and continues to grow (Benirschka & Binkley, 1994; PIantinga et al., 2002; Patton & McErlean, 2003; Huang et al., 2006; Livanis et al., 2006; Woodard, 2010; Baylis et al., 2011). This thesis contributes to that discussion by analyzing impacts of crop insurance on cash rents using county level panel data. Datasets with locational information have contributed to the growth of interest in spatial econometric methods. Identification strategies find both spatial structure (spatial heterogeneity) and spatial interactions (spatial autocorrelation) in the data used in this analysis. Therefore, the spatial model used incorporates relationships that exist through time and locations, and provides a more efficient estimate of the impacts of crop insurance on cash rents.

The analysis in this study examines 985 counties that fall within the 12 state Midwestern region of the United States. The United States Department of Agriculture (USDA) Economic Research

Service separates these 12 states into three different farm resource regions based on their specialization in production of farm commodities. These regions are the Corn Belt (Iowa, Illinois, Indiana, Ohio, and Missouri), the Lake States (Minnesota, Wisconsin, and Michigan), and the Northern Plains (North Dakota, South Dakota, Nebraska, and Kansas). These 12 states constituted $62.2 billion of the $99.3 billion (62.6%) in total liability in the crop insurance program in 2016 (RMA, 2017).

Critical input for this analysis originated from the *iFarm* Crop Insurance Decision Tool that the *farmdoc* team at the University of Illinois developed and maintains. Among other things, the *iFarm* Crop Insurance Decision tool uses a variety of different historical and current factors to calculate the long run expected "net cost of crop insurance" (net cost) to a producer. Differences in net costs arise due to mis-ratings, which producers can exploit in their crop insurance selection process.

This study employs a similar variable to net cost as a measurement of benefit to producers. Net value of crop insurance (net value) is calculated as compensation for damage or loss (indemnity) plus the portion of premium paid by the federal government (subsidy) minus the total premium. Dividing this value by total acres insured returns a per acre measure of the net value in any given year. When insurance is rated fairly, net cost equals the amount of subsidy.

Crop insurance impacts cash rents through two different mechanisms. First, producers may rebalance risk when purchasing crop insurance. Variation of returns represents one of the largest risks to producers when cash rents are negotiated. Crop insurance reduces variation of returns and therefore the producer's risk. Assuming that a producer has a certain risk tolerance, reduction in risk from crop insurance may result in risk being shifted to other areas of their operation to restore risk to its preferred level. Second, due to discernable patterns of net value, producers potentially factor net values into cash rents. This thesis focuses on that effect.

The results suggest that higher net value of crop insurance is associated with higher cash rental rates. In other words, as producers experience consistent excess benefits of crop insurance, they are willing to factor these benefits into cash rental rates. The consistency of payments plays a critical role in determining the portion of each dollar factored into rental rates. Because cash rents are sticky (Carson & Langemeier, 2017), producers require that net value from the crop insurance program be consistent before they factor expected net value into cash rents. As net value does become consistent through time and producer's expectations of the crop insurance program change, producers factor a statistically significant proportion of net value into rental rates. However, the economic significance of net value's impact presents a different story. Producers factor as much as \$0.01 of each additional \$1.00 in net value into cash rents, depending on the consistency of the payments. These findings represent a significantly smaller proportion in comparison to other forms of government payments, such as direct payments (Van Herck et al, 2013).

1.2 - Overview

This thesis is organized into six sections. Following this introduction, Chapter 2 provides background on the history and complexity of the federal crop insurance program. Chapter 3 reviews previous literature focused on farmland valuation and cash rents. Specifically, Chapter 3 traces the progression of the literature towards hedonic price models in farmland value analysis. Chapter 4 introduces the theory behind the model design and selection and discusses the data used in this analysis. Chapter 5 reports the results and discusses the potential implications. Finally, chapter 6 completes this thesis with a conclusion and discussion.

CHAPTER 2 - BACKGROUND

Agricultural economists have studied the effects of government programs on farmland values dating back to the mid-1960s (Herdt & Cochrane, 1966). Similar to previous federal agriculture programs, crop insurance faces public scrutiny. The scrutiny has intensified as public subsidies for crop insurance have grown over the past decade. Crop insurance subsidies, farm real estate prices, and cash rents have each more than doubled during the past two decades across the Midwest. As a result, many suspect crop insurance plays a causal role in the increase in land values and cash rents. Figures 1-4 show trends in land values, cash rents, and crop insurance subsidies. Subsidies for federal crop insurance in the 2016 crop year were $6.89 billion of the $9.08 billion in total premium, while producers paid the remainder (RMA, 2017). As of 2016, farm real estate in the United States is valued at over $2.4 trillion, representing over 80% of all farm assets (USDA, 2017).

Figures 1-3 display trends in land values, cash rents, and year-over-year changes in land values. On average, the Corn Belt experienced the largest increases, gaining over $4,000 per/acre in value between 2000 and 2016. Northern Plains land values experienced the widest range of percent changes during the same period, from increases of 26.89% in 2012 to decreases of 5.94% in 2016. As expected, rent values follow a similar path to farmland values, experiencing the rapid rise followed by a slow decline. Myriad factors affect farmland values though, whereas expected income is the main driver of cash rents.

The capitalization rate of farmland is a common measure of the relative price of farmland. Calculated by dividing yearly rent by total value, the capitalization rate measures the amount buyers pay for current earnings to farmland. Schnitkey (2016) shows strong correlation between capitalization rates and the U.S. ten-year treasury yield. Intuitively this is understandable, as raising interest rates increases financing costs while also offering an investment alternative.

Cash rent leasing agreements continue to increase in popularity across the Midwest. Data from the Illinois Farm Business Farm Management (FBFM) Association show cash rented farmland increased from 40% to 43% of total farmland between 2010 and 2015 (FBM, 2016). Producers benefit most from cash rent leasing agreements during favorable growing seasons when realized revenue exceeds the expected revenue amount. However, because cash rents are fixed costs, producers bear all the risk during inferior growing seasons.

Producers consider an array of factors when establishing rental agreements with property owners. These factors include land productivity, the variability of those crop returns, field size and shape, drainage, ease of access, market access, local market prices, potential for wildlife damage, field perimeter characteristics, competition for rented cropland in a region, and crop insurance (Ward, 2015).

2.1 - Crop Insurance: History and Performance

Agriculture production is an inherently risky business whereby producers face a variety of production impediments ranging from adverse weather and pests to natural disasters such as fire (Goodwin & Smith, 1995). The frequency of adverse events coupled with their severity led directly to the creation of a federal crop insurance program in the 1930s. Enacted in 1938, the Crop Insurance Act was a direct response to the Dust Bowl and Great Depression. The initial crop insurance program insured only yields. High premiums and low participation rates hindered the growth of the program to such an extent that Congress discontinued federal crop insurance in 1943 before reenacting it in 1945.

Low participation rates continued to plague the program though until the Crop Insurance Act of 1980. This act introduced premium subsidies and expanded the availability of crop insurance to additional crops and regions of the country. Congress initially capped premium subsidies at 30% of the premium at the 65% coverage level. While participation levels increased, the need for congress to issue *ad hoc* disaster payments after adverse events persisted. As disaster relief payments became annualized and larger, incentives to participate in the voluntary federal crop insurance program were further diminished (Goodwin & Smith, 1995).

Beginning in the early 1990's, proponents of crop insurance criticized the "annual" *ad hoc* disaster relief programs. They placed blame directly on *ad hoc* payments for competing with Federal Crop insurance, and lobbied for change. Congress responded with the Federal Crop Insurance Reform Act of 1994. One of the many changes, this Act required producers participate in the federal crop insurance program to be eligible for other federal agriculture programs such as deficiency payments and certain loan programs.

Catastrophic (CAT) crop insurance originated with the 1994 Act. CAT crop insurance offers a minimal cost alternative for producers who want the minimal amount of coverage while remaining eligible for federal benefits. The federal government completely subsidizes premiums for CAT, while producers pay a onetime service fee for each crop they grow, in each county grown. CAT coverage compensates producers for crop yield losses that exceed 50% of historical yield at a rate of 55% of the projected season average market price.

Following the 1994 Act, participation in the Federal crop insurance program increased drastically, with enrolled acres more than doubling from roughly 100 million in 1994 to over 220 million in 1995. As the program grew, the Risk Management Agency (RMA) was created to administer Federal Crop Insurance Corporation (FCIC) programs and other non-insurance-related risk management and education programs that help support U.S. agriculture.

In 2000, Congress raised the subsidy rates and made several changes to RMA, including allowing them to enter into contracts or partnerships with private entities that developed and maintained crop insurance products. The public-private partnerships expanded the number and quality of crop insurance products offered to producers.

The price of premiums encompasses the most important factor when deciding whether to participate in crop insurance (Sherrick et al., 2003). However, price is only one facet of the selection process. Individual producer characteristics, such as risk tolerance, also influence a producer's decision. Kirwan (2014) finds that farm operators that purchase crop insurance tend to be younger and more highly educated than operators who forgo crop insurance. Farms with crop insurance also tend to have higher revenues and leverage compared to their counterparts. While leverage refers to financed debt, cash rental agreements represent a significant financial obligation not recorded on farm balance sheets. Accordingly, Sherrick et al (2003) find that among many factors, cash rental obligations play an important role in the crop insurance selection process.

Currently, crop insurance protects over 297 million acres of farmland with an insured liability of over $99 billion (RMA, 2017). The two categories of crop insurance used today are yield and revenue insurance. Revenue insurance combines the production guarantee of yield-based policies and a price guarantee to create an instrument that protects against revenue loss from deficient yields, price declines, or both. RMA introduced revenue insurance in 1996 to corn and soybean producers in Nebraska and Iowa. Revenue insurance quickly became a favorite of producers and RMA expanded its availability to the rest of the country by 2003. Of the 2.07 million crop insurance policies sold in 2016, revenue-based policies accounted for 74% (1.54 million).

Table 1 displays the subsidy rates schedule for federal crop insurance as of 2016. Other than for catastrophic crop insurance, coverage levels play an important role in determining subsidy rates. Tables 2 – 4 display descriptive statistics of the federal crop insurance program, sorted first by year, and then by the states analyzed in this thesis. The tables show that premiums, subsidies, and indemnity payments all trended upwards the past two decades before shrinking slightly the past few years. The price-level effect of commodities explains much of the increase in size of all three. The cost of insurance closely tracked commodity prices upwards as corn, wheat, and soybean prices soared in the mid-to-late 2000's. Because subsidies are calculated as a proportion of total premiums, subsidies grew as premiums grew.

2.2 - Federal Crop Insurance Subsidies

Economists agree that increasing the subsidy rates for crop insurance led directly to the growth of the program, but they disagree about why and if subsidies are needed (Zulauf, 2016). While proponents of crop insurance endorse its effectiveness at reducing variation in agricultural returns, opponents rally against subsidizing a program plagued by systemic risk, moral hazard, and adverse selection. Proponents of the subsidy point out the need for widespread enrollment in the program to achieve a functioning insurance market. Insurance markets function best when non-systemic risks are spread across a pool of risk averse individuals (Goodwin & Smith, 1995). Diversifying away all risk in crop insurance markets remains difficult though, as adverse events, like droughts, are often not correlated across insured units. For example, if a drought adversely affects one field, it most likely affects neighboring fields as well. Systemic risk is the remaining risk that cannot be diversified away. While private markets currently offer products for idiosyncratic risks such as hail or crop fire, up to 50% of the total risk in crop production is systemic risk (Zulauf et al., 2013). The scale of the systemic risk issue makes establishing a successful private insurance market for multi-peril crop insurance difficult. Subsidies therefore help maximize the number of farms to spread the risk across by increasing participation in the program.

Opponents argue that asymmetric information exists between the party who establishes the premiums and the producers who purchase the insurance. In crop insurance markets, asymmetric information can lead to a tendency for only high-risk producers to purchase crop insurance. Economists define this scenario as adverse selection. Previous literature notes the cost of crop insurance as the main participation inhibitor of the program in the first five decades of its existence. Adverse selection had a significant impact on the actuarially soundness of premium rates for this period (Miranda, 1991). Low-risk producers avoided purchasing crop insurance due to its high cost, only to cause insurance premiums to rise. The remaining two types of producers who purchased crop insurance were extremely risk-averse and high-risk producers. Insuring high-risk producers kept premiums high, which further prevented low-risk producers from enrolling in the program.

The federal government requires crop insurance participation to be eligible for other federal programs and utilizes subsidies to invoke low-risk producers to participate in the program, but adverse selection remains. Makki and Samwaru (2001) find informational asymmetries in the crop insurance market lead to federal crop insurance overcharging high-risk producers and undercharging low-risk producers for comparable insurance contracts. Drain tile, irrigation, and other unaccounted for growing practices further enhance producers' ability to distinguish their individual risk compared to others. Crop insurance products that address these different growing practices may further reduce adverse selection in crop insurance.

A lack of desire may also exist among producers to guard themselves against risk once insured against its consequences, otherwise referred to as moral hazard. Hölmstrom (1979) more formally defines moral hazard as the situation that arises when individuals engage in risk sharing under conditions such that their privately taken actions affect the probability distribution of the outcome. Once producers purchase crop insurance, they may alter their risk tolerance in other areas of their operation as a form of risk rebalancing. A 1996 study by Goodwin and Smith finds that Kansas wheat producers who purchase crop insurance use less fertilizer and chemicals than those who do not purchase crop insurance. The premium rates generated for these producers are subsequently inefficient once these producers alter their production practices.

Two alternatives to crop insurance subsidies include diversification of risk through international reinsurance markets, or using weather derivatives as primary crop insurance instruments. Currently, the United States federal government acts as a reinsurer to companies offering crop insurance products to producers. Due to the size of international reinsurance markets, the possibility exists to diversify away systemic risk that exists in domestic crop insurance markets. Vedenov and Barnett (2004) analyze the use of weather derivatives as primary crop insurance instruments with results that vary widely based on product and region combinations. Furthermore, the complexity of the combinations of weather variables impedes the commercialization of this proposed solution.

Crop insurance subsidies remain a highly-debated aspect of the Farm Bill (Zulauf, 2016). However, one point of agreement is that government payments can affect farmland values (Shoemaker, 1989; Goodwin and Ortalo- Magné, 1992; Veeman et al, 1993; Nickerson et al, 2012). The proportion of government payments that producers capitalize into farmland values varies depending on the delivery method of the government payment. Using computable general equilibrium modeling, Shoemaker et al (1990) find long-run equilibrium cropland values would be 15% to 20% lower in the absence of government payments from farm programs. Goodwin and Ortalo-Magné (1992) construct a subsidy equivalent variable for three regions: United States, France, and Canada. They find a 1.0% increase of the subsidy equivalent results in a 0.38% increase in farmland values. Veeman et al (1993) looks at the proposal to remove all government subsidies paid directly to producers and finds land values would decrease by an average of 19%. Interestingly, the projected reduction in farmland values varies widely by region. For example, Ontario farmland value projections show a decline of 12.2% while

Saskatchewans projected decline was 29.9%. Alternatively, Langemeier (2013) finds that indemnity payments from subsidized yield-protection crop insurance have no significant effect on cash rents or land values.

Economists argue in favor of policies that do not link payments to output or factors of production, however these policies are difficult to achieve in practice (Hennessy, 1998). Established during the Uruguay Round Reform of 1974, the World Trade Organization (WTO) requires agricultural support programs to producers do not influence the type or quantity of production (decoupled). Direct payments to producers is one form of a decoupled agricultural program. In 1996, direct payments replaced previous price support programs and brought US agriculture into compliance with WTO rules for agriculture. Intended only to help producers transition to commodity markets driven purely by supply and demand, the 2002 Farm Bill solidified the permanence of direct payments with the creation of the Direct and Counter-cyclical Payment Program (DCP). DCP remained for a decade until the 2012 Farm Bill, when support ceased for direct payments to producers amid an era of historically high farm incomes.

The lump sum principle from utility maximization theory illustrates why economists favor direct payments to producers. With direct payments, a producer allocates their additional resources in a way that maximizes their specific utility. Because each producer maximizes their utility in a different manner, money transferred to producers via direct payments maximizes the sum total utility of all producers. With crop insurance subsidies, producers never explicitly control the money that goes towards subsidizing their crop insurance. They implicitly receive the dollar amount of their subsidy via a reduction in premium rates, and the government transfers that money directly to crop insurance companies. If RMA rates crop insurance fairly, the value of the subsidy represents the expected net value to a producer in any given year. To verify if this condition exists, an analysis of the historical loss performance of crop insurance follows.

2.3 - Loss Ratios

A common method used to analyze loss performance of crop insurance is to calculate loss ratios. Loss ratios measure the amount of money paid to producers via indemnity payments compared to the total premium. Note, total premium is the sum of producer paid premium and government paid premium subsidies. The Farm Bill requires the Federal Crop Insurance Program have a loss ratio objective of not greater than 1.0, or the actuarially fair premium rate. A loss ratio greater than one therefore implies the producer received more than the producer paid premium plus the subsidy. Loss ratios in crop insurance tend to vary drastically through time, but cluster spatially in any given year, due to the spatial nature of large-scale weather phenomena, such as droughts.

Loss ratios over a period are either average loss ratios (ALR) or total loss ratios (TLR). ALRs are a simple average of yearly loss ratios for the period, while TLRs are calculated by dividing the sum totals of indemnities and premiums from the entire period. The different calculations account for differences in the scale of the crop insurance program through time. For example, we can consider the same county in the Midwest twenty years apart. Inflation aside, a loss ratio of 1.5 in 1995 would not require nearly the size indemnity payout as a loss ratio of 1.5 in 2016. This results from both the participation rate and the average level of coverage increases. A simple average of loss ratios from 1995 through 2016 therefore gives disproportionate weight to earlier years when the program was significantly smaller. Additionally, adverse selection played a greater role in crop insurance prior to subsidy rate increases. Older loss ratios therefore may reflect the difficulty in rating high-risk producers only, and may not be useful in rating insurance products today.

Figures 5 and 6 display ALRs and TLRs, respectively, for the period 1995-2016 in the Midwest. Dependent on the loss ratio used, the two pictures illustrate similar loss experiences for some counties and vastly different loss experiences for others. For example, both maps show Northcentral Illinois on average experienced loss ratios below one for the period, while areas such as Northwest Minnesota experienced ALRs greater than one for the period. However, counties in Northwest Minnesota paid more in total premium than indemnity payments paid out over that period though as illustrated by the TLRs. Analysis of the data shows that crop insurance grew drastically over the period of 1995-2016 in Northwest Minnesota, with many loss ratios below one occurring later in the period.

For comparison, Figures 7 – 12 show ALR and TLR for corn, soybeans, and wheat individually. Corn, soybeans, and wheat represent the majority of acres insured by federal crop insurance in the Midwest. These maps illustrate that a wide variation in loss experience exists among different crops, even within same counties. Barnard et al (1997) find similar effects from the commodity support program payments on cropland values. Barnard et al find the effects vary spatially based on program differences and the agronomic flexibility producers have to grow alternative crops. These effects result in cash rents that are more responsive to government payments in certain areas.

The ALR and TLR maps reveal often the highest (lowest) loss ratios occur near state borders. The observation of high loss ratios near state borders perhaps reflects historical difficulties rating crop insurance products using statewide parameters. Risk characteristics for the entire state perhaps do not accurately apply to fringe counties, as arbitrary state lines were often established using natural features such as rivers.

Yearly loss ratio maps for the period 1995-2016 are attached in Appendix A as A1 – A22. These maps illustrate how losses are largely regional in any given year. As discussed previously, the spatial nature of losses in any given year represents a significant obstacle for private insurance companies whose business model relies on the diversification of risk. A18 displays the effects of the drought of 2012 that affected many of the Midwest counties. Federal crop insurance paid out over $13.4 billion in indemnity payments to producers in 2012 alone in the 985 counties in this analysis. Conversely, the same 985 counties received just over $1.09 billion in indemnity payments in 2016, as displayed in A22. Table 2 provides a year-by-year reference of average premiums, subsidies, and indemnity payments.

<u>2.4 – Tables and Figures</u>

Figure 1:

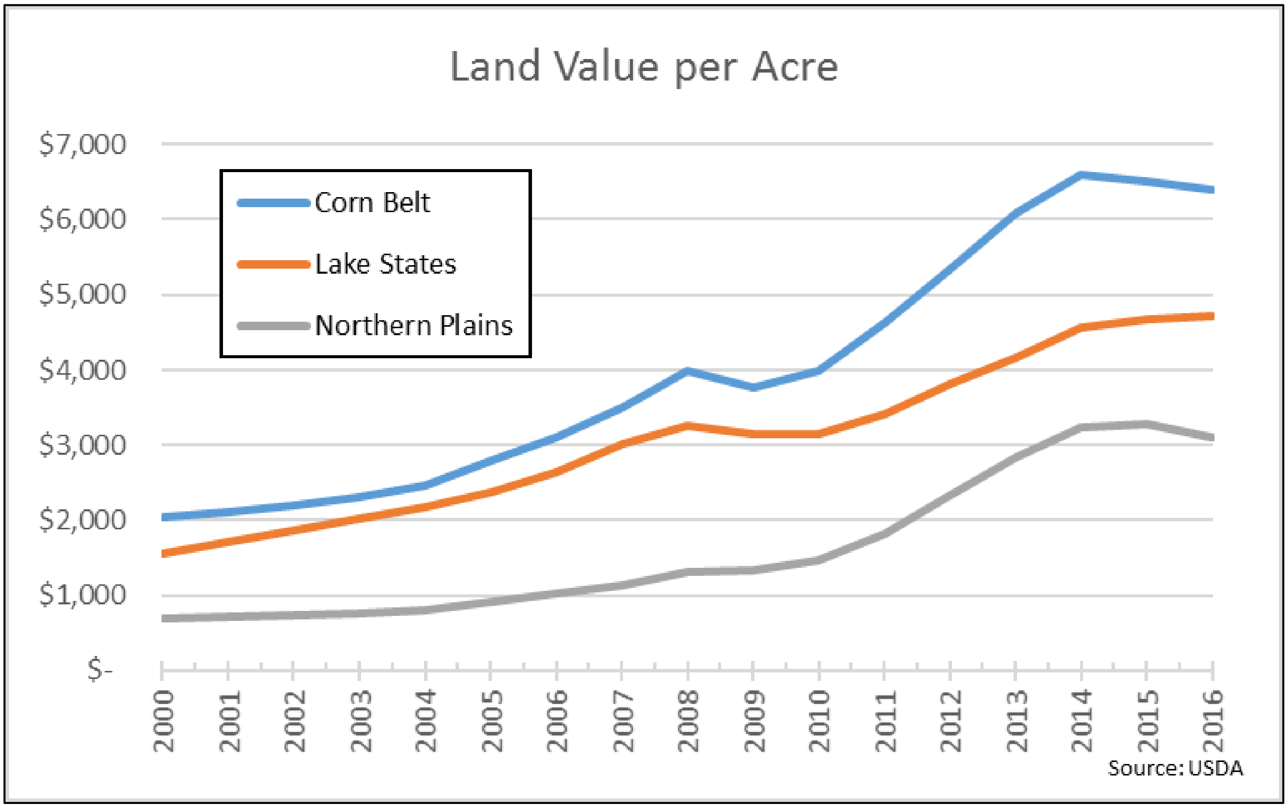


Figure 2:

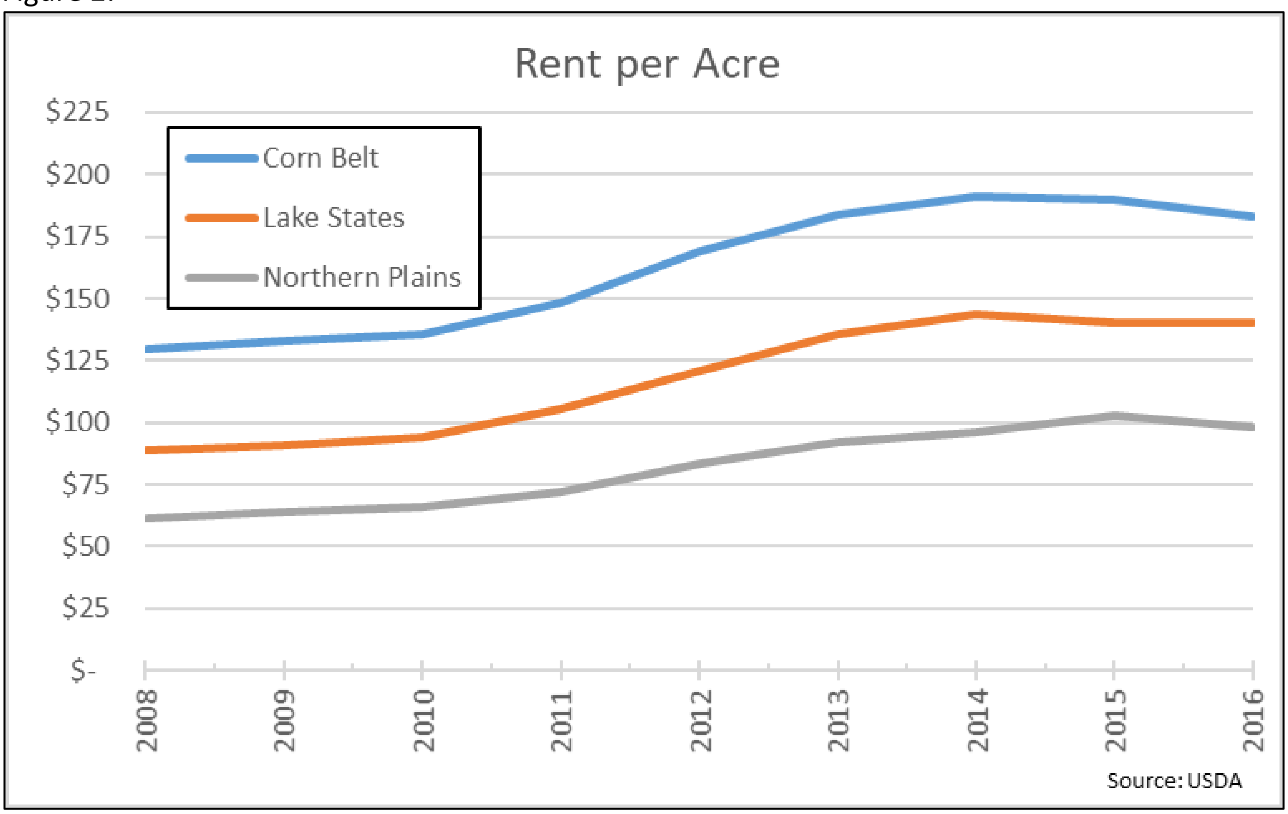


Figure 3:

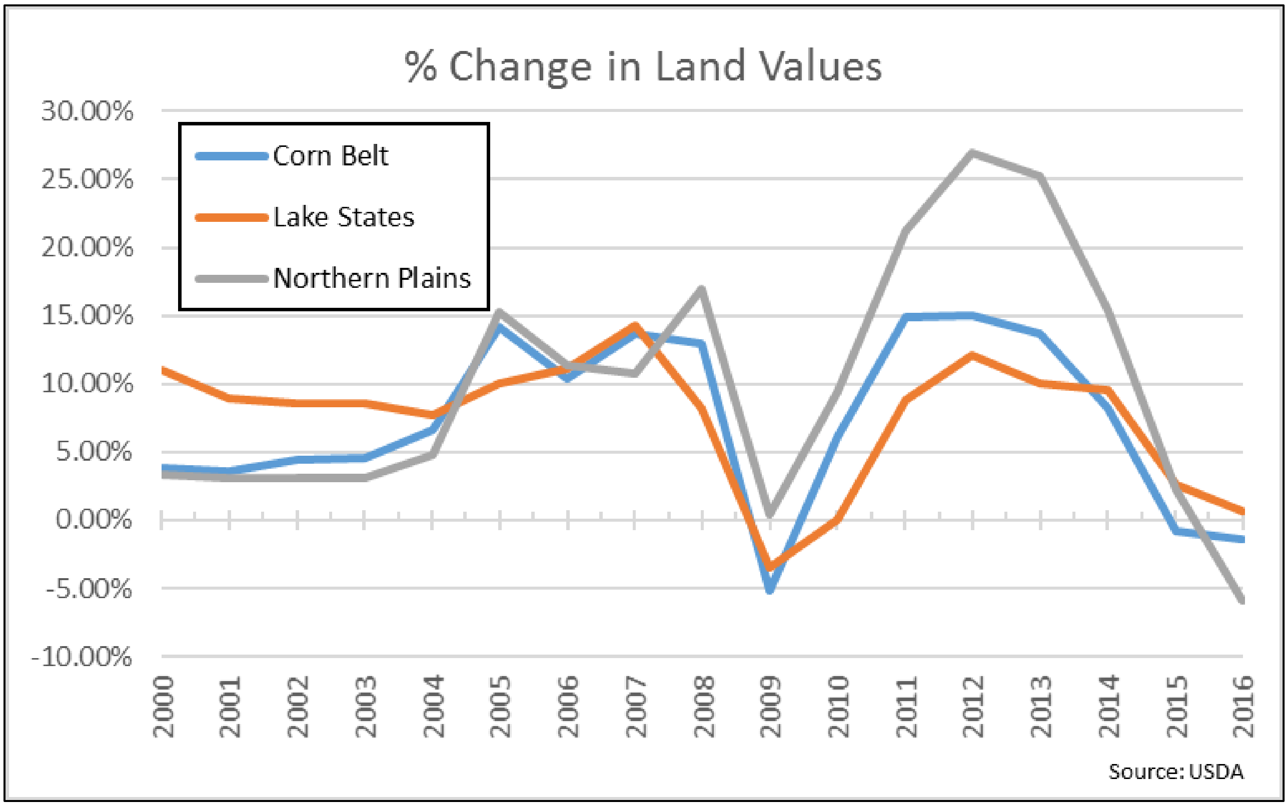


Figure 4:

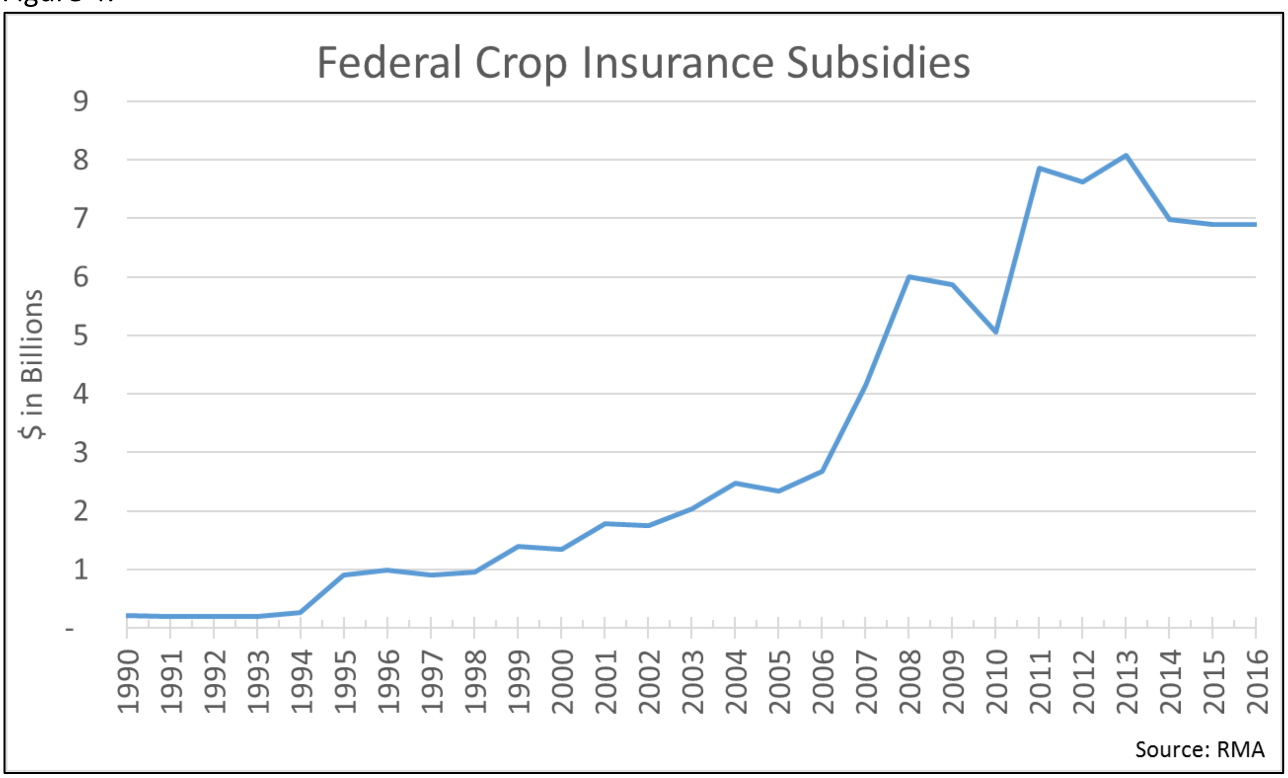


Table 1:

Subsidy Rate (%) for Crop Insurance Premiums									
Insurance Plan	Coverage Level (%)								
	CAT	50	55	60	65	70	75	80	85
Basic and Optional Units	100	67	64	64	59	59	55	48	38
Enterprise Units	-	80	80	80	80	80	77	68	53
Area Yield Plans	-	-	-	-	-	59	59	55	55
Area Revenue Plans	-	-	-	-	-	59	55	55	49
Whole Farm Units	-	80	80	80	80	80	80	71	56

Notes: CAT = Catastrophic Insurance, "-" = not applicable

Source: RMA

Table 2:

	Premium/Acre		Subsidy/Acre		Indemnity Payments/Acre	
	Average	Standard Deviation	Average	Standard Deviation	Average	Standard Deviation
1995	$10.02	$8.93	$3.93	$3.00	$11.47	$22.27
1996	$13.25	$15.12	$5.02	$4.32	$13.75	$27.98
1997	$12.9	$16.39	$4.79	$4.73	$6.99	$19.67
1998	$13.47	$16.97	$4.96	$5.12	$10.41	$31.33
1999	$13.68	$13.88	$7.25	$7.41	$11.7	$28.06
2000	$13.93	$10.09	$6.41	$5.06	$11.06	$20.63
2001	$15.28	$9.59	$8.56	$5.26	$13.97	$23.33
2002	$15.13	$9.09	$8.44	$5.19	$23.35	$36.59
2003	$17.6	$9.15	$9.8	$5.37	$19	$20.59
2004	$21.9	$8.75	$12.27	$5.12	$18.77	$21.45
2005	$19.89	$6.92	$11.14	$4.06	$10.7	$14.5
2006	$23.1	$9.95	$12.9	$5.68	$12.01	$16.52
2007	$34.82	$11.44	$19.47	$6.5	$19.43	$25.74
2008	$52.61	$12.54	$29.16	$6.88	$53.8	$41.77
2009	$43.09	$11.11	$25.45	$6.6	$17.48	$19.32
2010	$35.77	$11.1	$21.57	$7.07	$19.87	$27.44
2011	$55.66	$15.28	$33.97	$9.88	$39.14	$46.55
2012	$48.9	$12.54	$30.32	$8.63	$105.43	$100.82
2013	$50.32	$12.6	$30.58	$9.1	$49.59	$46.5
2014	$42.41	$13.44	$25.76	$9.56	$35.53	$35.14
2015	$41.28	$14.53	$25.42	$10.42	$25.12	$34.53
2016	$38.65	$18.28	$24.14	$12.99	$8.55	$9.86

Source: RMA SOB

Table 3:

Premium per Acre - Average

	2000	2001	2002	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016
IA	$ 12.15	$ 13.10	$ 12.68	$ 14.00	$ 19.08	$ 16.38	$ 18.94	$ 30.75	$ 45.96	$ 36.01	$ 28.43	$ 48.53	$ 41.93	$ 42.91	$ 33.35	$ 32.69	$ 27.34
IL	$ 13.15	$ 14.04	$ 13.78	$ 15.69	$ 20.17	$ 18.87	$ 26.16	$ 39.42	$ 54.87	$ 42.66	$ 33.64	$ 54.00	$ 44.32	$ 43.73	$ 35.73	$ 36.17	$ 32.86
IN	$ 15.84	$ 16.30	$ 15.49	$ 17.96	$ 24.00	$ 22.40	$ 26.28	$ 40.38	$ 60.23	$ 48.32	$ 38.10	$ 61.51	$ 51.33	$ 50.93	$ 40.76	$ 39.86	$ 36.37
KS	$ 8.80	$ 11.29	$ 11.46	$ 13.59	$ 16.70	$ 16.50	$ 18.49	$ 27.92	$ 41.41	$ 44.22	$ 32.15	$ 46.84	$ 45.67	$ 47.06	$ 37.22	$ 34.77	$ 32.65
MI	$ 16.13	$ 16.80	$ 16.70	$ 18.51	$ 22.97	$ 23.66	$ 25.32	$ 36.90	$ 54.03	$ 46.28	$ 38.91	$ 59.10	$ 52.18	$ 50.74	$ 45.30	$ 44.23	$ 42.91
MN	$ 12.94	$ 14.47	$ 14.63	$ 16.96	$ 21.79	$ 18.50	$ 20.60	$ 32.85	$ 52.66	$ 37.88	$ 31.72	$ 50.30	$ 47.94	$ 47.37	$ 37.53	$ 35.87	$ 32.04
MO	$ 14.90	$ 15.96	$ 15.10	$ 18.20	$ 23.42	$ 20.28	$ 23.56	$ 34.72	$ 53.10	$ 42.86	$ 36.83	$ 56.94	$ 48.75	$ 50.03	$ 44.09	$ 43.90	$ 40.61
ND	$ 10.35	$ 11.28	$ 11.32	$ 14.33	$ 16.86	$ 15.39	$ 19.17	$ 26.41	$ 51.47	$ 33.35	$ 31.35	$ 50.12	$ 45.67	$ 51.24	$ 42.22	$ 39.58	$ 38.98
NE	$ 11.84	$ 14.58	$ 14.40	$ 17.26	$ 20.54	$ 18.37	$ 21.03	$ 32.20	$ 47.97	$ 40.10	$ 31.70	$ 50.27	$ 43.76	$ 45.29	$ 36.08	$ 34.56	$ 31.37
OH	$ 12.12	$ 13.13	$ 13.08	$ 15.86	$ 20.57	$ 19.61	$ 23.18	$ 34.34	$ 53.52	$ 44.64	$ 35.50	$ 58.37	$ 47.97	$ 47.31	$ 38.74	$ 36.72	$ 34.35
SD	$ 10.51	$ 12.01	$ 12.05	$ 15.16	$ 19.03	$ 17.26	$ 20.00	$ 31.55	$ 49.92	$ 40.39	$ 34.56	$ 51.81	$ 49.88	$ 56.79	$ 49.87	$ 48.85	$ 47.65
WI	$ 15.19	$ 17.24	$ 18.04	$ 20.27	$ 24.25	$ 22.77	$ 25.97	$ 40.53	$ 58.58	$ 48.79	$ 43.14	$ 64.21	$ 55.68	$ 55.41	$ 49.42	$ 47.86	$ 43.06

Source: RMA

Table 4:

Subsidy per Acre - Average

	2000	2001	2002	2003	2004	2005	2006	2007	2008
IA	$ 4.82	$ 6.94	$ 6.66	$ 7.42	$ 10.22	$ 8.75	$ 10.08	$ 16.41	$ 24.62
IL	$ 5.17	$ 7.34	$ 7.15	$ 8.17	$ 10.71	$ 9.99	$ 13.93	$ 20.88	$ 27.75
IN	$ 6.00	$ 8.42	$ 7.99	$ 9.31	$ 12.64	$ 11.86	$ 13.92	$ 21.44	$ 30.75
KS	$ 4.32	$ 6.49	$ 6.56	$ 7.71	$ 9.51	$ 9.46	$ 10.60	$ 16.07	$ 23.97
MI	$ 7.95	$ 9.67	$ 9.43	$ 10.42	$ 12.96	$ 13.40	$ 14.24	$ 20.68	$ 29.40
MN	$ 6.00	$ 8.11	$ 8.06	$ 9.38	$ 12.12	$ 10.19	$ 11.37	$ 17.96	$ 29.23
MO	$ 7.13	$ 9.25	$ 8.67	$ 10.39	$ 13.49	$ 11.69	$ 13.49	$ 20.00	$ 30.64
ND	$ 5.05	$ 6.41	$ 6.48	$ 8.18	$ 9.71	$ 8.88	$ 11.10	$ 15.32	$ 29.99
NE	$ 5.16	$ 7.98	$ 7.89	$ 9.44	$ 11.39	$ 10.23	$ 11.71	$ 18.09	$ 27.23
OH	$ 5.07	$ 7.12	$ 7.02	$ 8.39	$ 11.01	$ 10.51	$ 12.41	$ 18.56	$ 28.33
SD	$ 5.16	$ 7.00	$ 6.98	$ 8.73	$ 11.02	$ 10.04	$ 11.63	$ 18.31	$ 29.09
WI	$ 7.33	$ 9.91	$ 10.31	$ 11.61	$ 13.84	$ 12.92	$ 14.70	$ 22.92	$ 32.72

	2009	2010	2011	2012	2013	2014	2015	2016
IA	$ 20.48	$ 16.37	$ 27.62	$ 24.18	$ 23.01	$ 17.38	$ 17.13	$ 14.50
IL	$ 23.00	$ 18.49	$ 30.00	$ 25.09	$ 24.11	$ 19.61	$ 20.24	$ 18.54
IN	$ 25.71	$ 20.78	$ 33.63	$ 28.74	$ 27.76	$ 22.25	$ 22.16	$ 20.26
KS	$ 26.13	$ 19.37	$ 28.57	$ 27.62	$ 28.33	$ 22.46	$ 21.28	$ 20.15
MI	$ 27.56	$ 23.87	$ 37.31	$ 33.89	$ 32.56	$ 28.76	$ 28.18	$ 27.67
MN	$ 22.88	$ 19.41	$ 31.22	$ 29.74	$ 28.78	$ 22.30	$ 21.48	$ 19.51
MO	$ 26.86	$ 23.39	$ 36.98	$ 31.70	$ 31.83	$ 28.09	$ 28.11	$ 26.43
ND	$ 20.59	$ 19.59	$ 31.84	$ 29.49	$ 33.29	$ 27.65	$ 26.50	$ 26.59
NE	$ 23.53	$ 18.81	$ 29.78	$ 25.98	$ 25.13	$ 19.93	$ 19.48	$ 17.98
OH	$ 25.33	$ 20.54	$ 34.01	$ 28.81	$ 27.98	$ 22.99	$ 22.06	$ 20.56
SD	$ 25.81	$ 22.46	$ 34.34	$ 33.78	$ 37.97	$ 33.89	$ 33.98	$ 33.66
WI	$ 29.28	$ 26.36	$ 40.46	$ 36.03	$ 35.05	$ 31.13	$ 30.65	$ 27.84

Source: RMA

Figure 5:

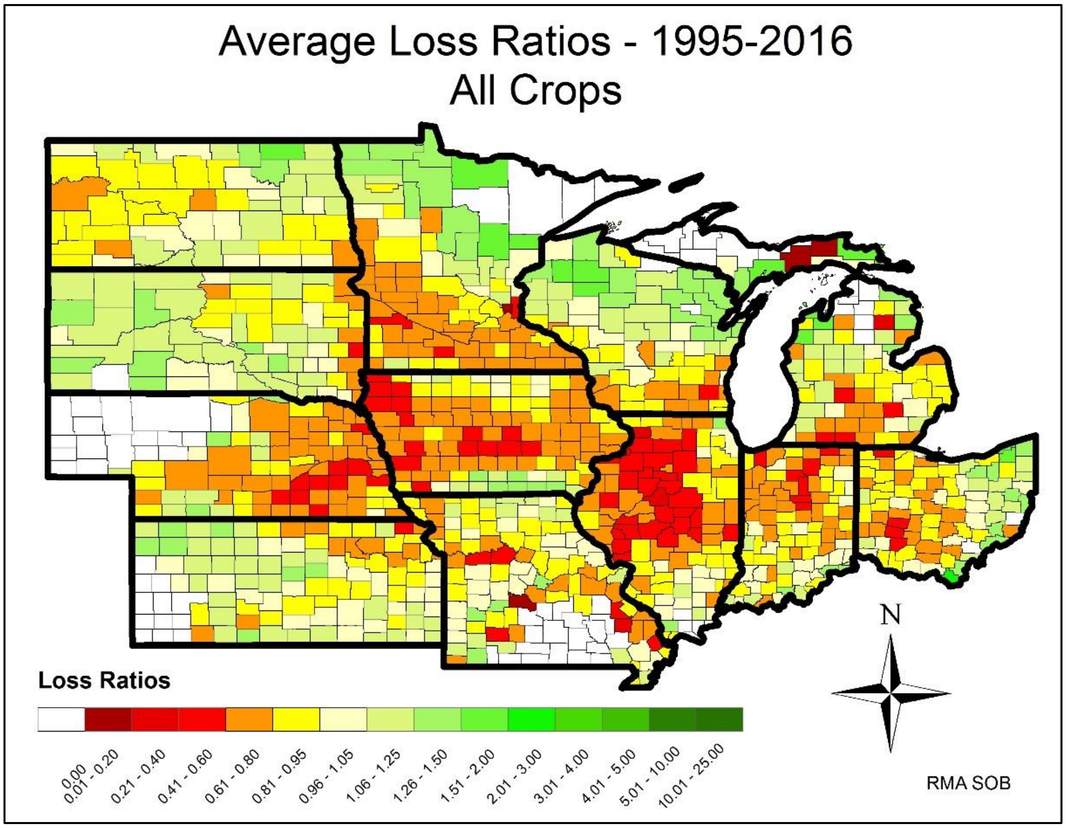


Figure 6:

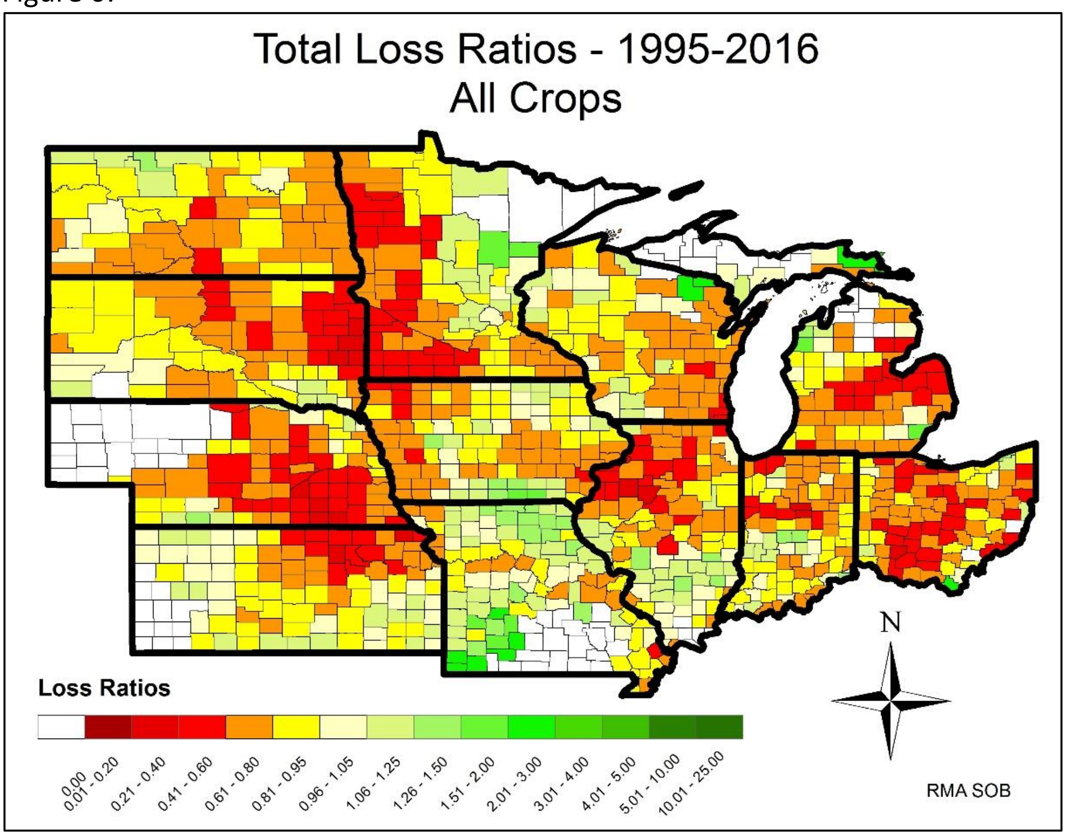


Figure 7:

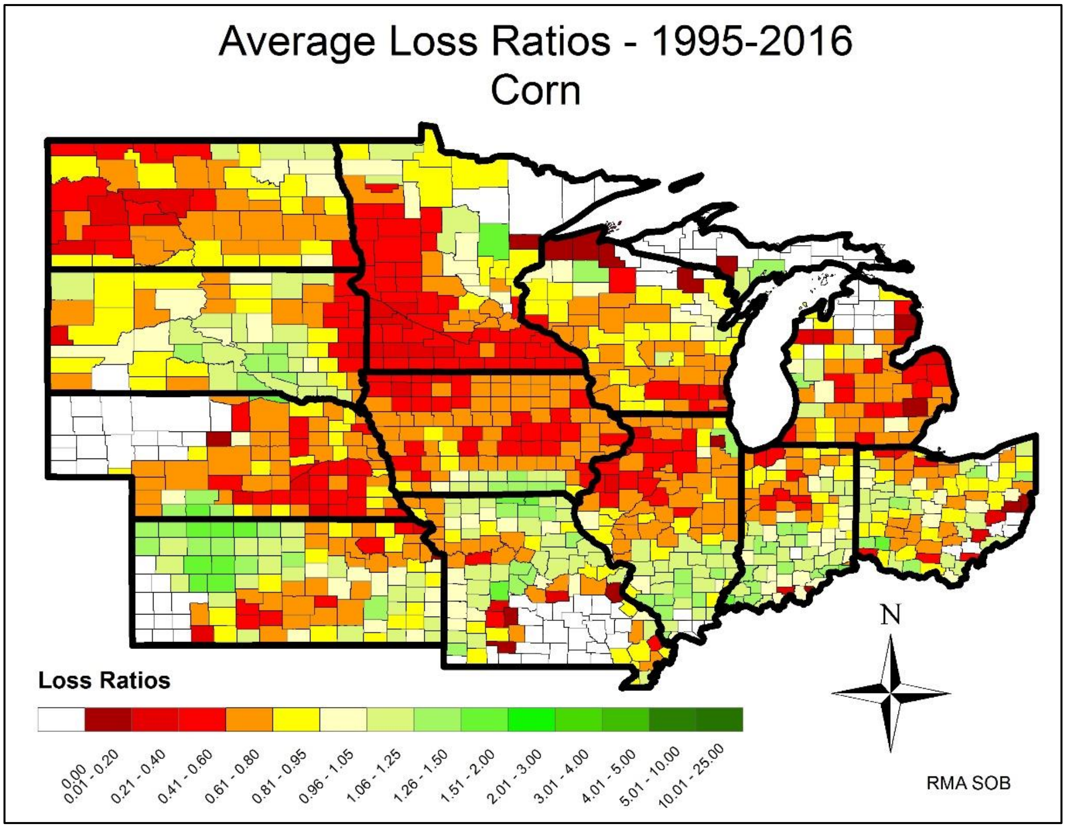


Figure 8:

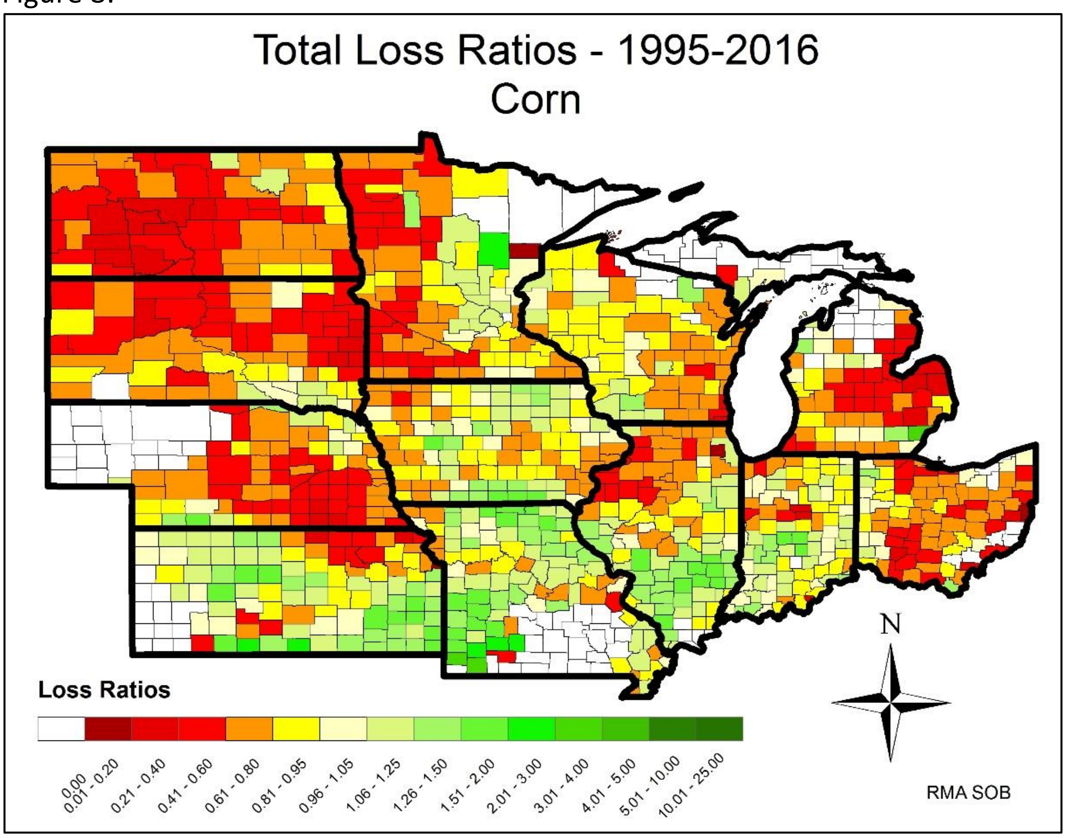


Figure 9:

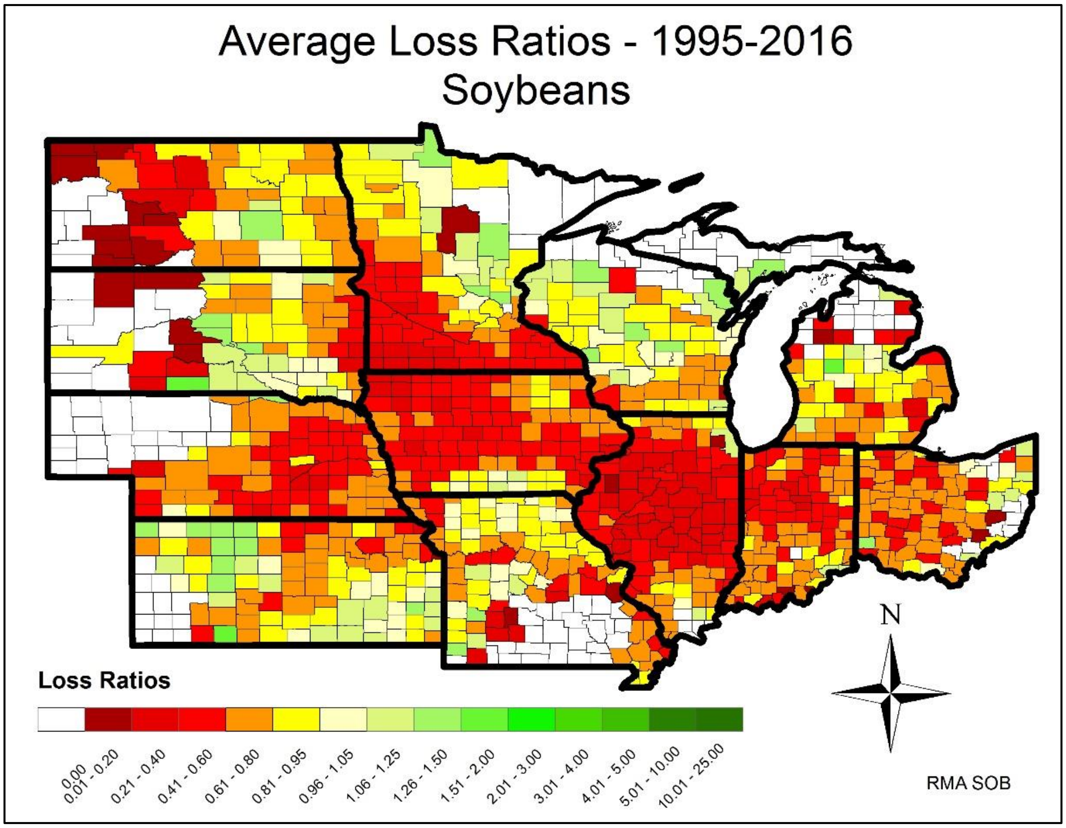


Figure 10:

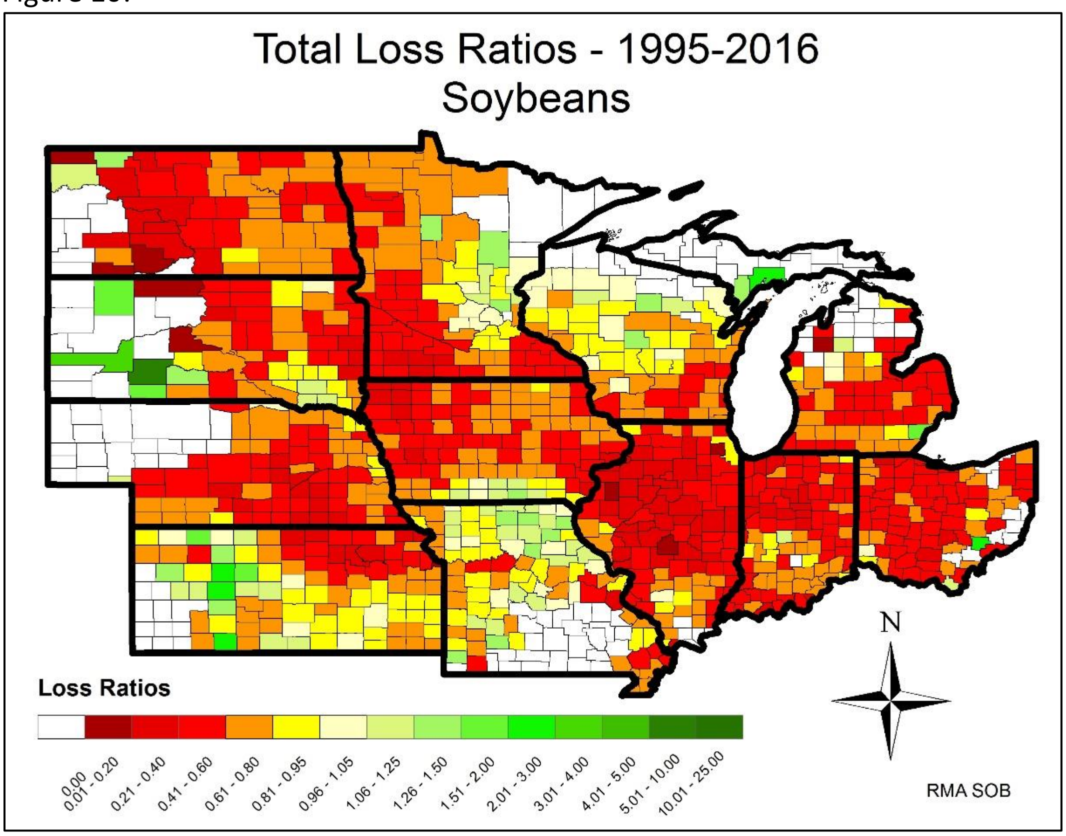


Figure 11:

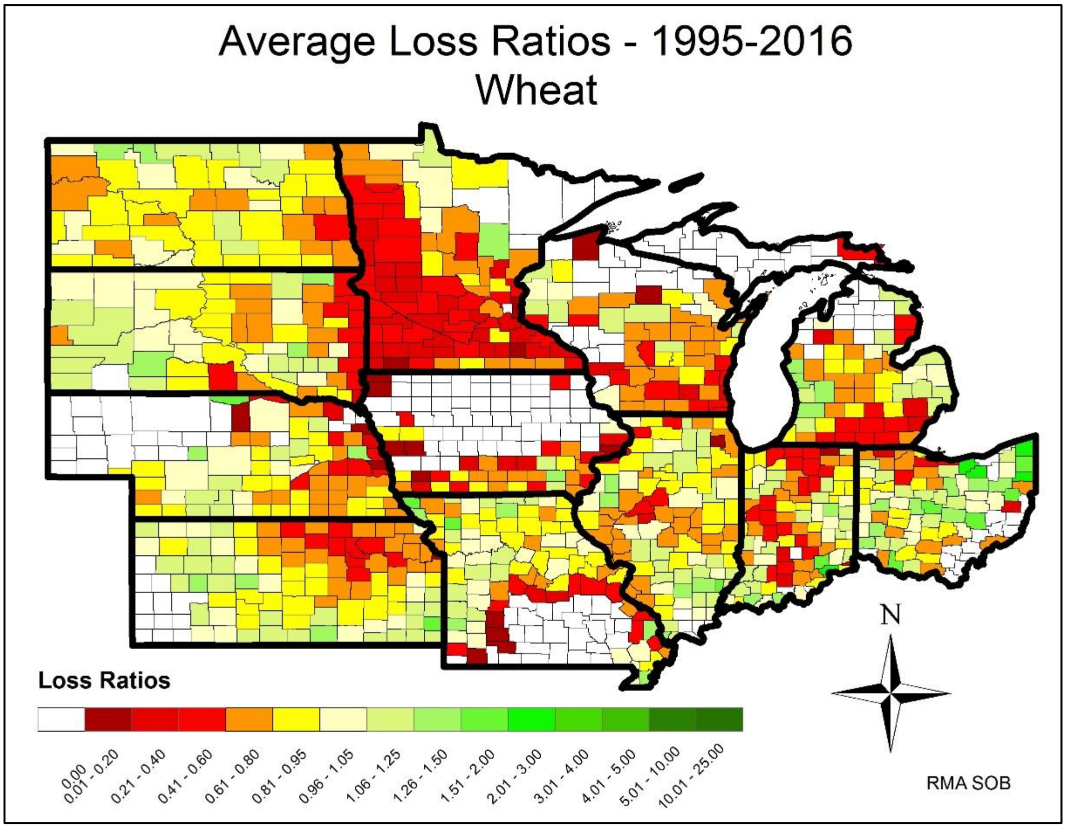
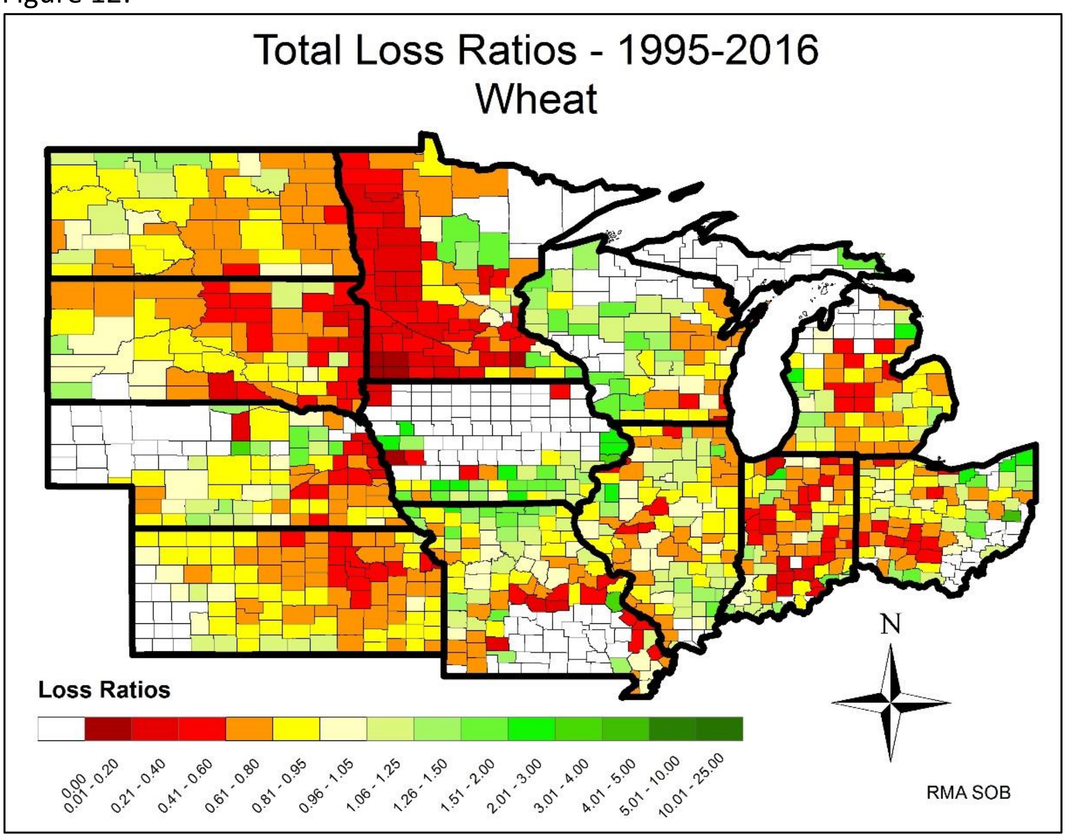


Figure 12:



CHAPTER 3 – LITERATURE REVIEW

3.1 - Historical Land Value Theory

There exists a very developed discussion about farmland values and many of those insights apply to cash rents paid for farmland. Soil quality, drainage, and proximity to markets constitute a few of the factors that affect farmland values and cash rents alike. Schnitkey and Sherrick (2011) explore the relationship between cash rents and farmland values more thoroughly, and the two values are highly correlated. Subsequently, a comprehensive historical analysis is warranted.

Ricardo (1821) established the earliest theory of the value of land. "Ricardian Rent Theory" postulates that rent equals the surplus in production realized on superior soil in comparison to production on inferior soils. In his example, Ricardo imagines a newly settled country with a small population. Figure 13 below illustrates the hypothetical situation. The initial settlers begin farming only the highest quality of land, Type A, which yields the largest quantity of production, 80. As the countries' population grows, increase in demand raises the price to a point where farming inferior land, Type B, is economically feasible to cultivate and farm. Ricardo determined rent to be the difference in production on Type A land versus Type B. Figure 13 illustrates that rent equals 20 units of production. Furthermore, residents will bring additional land into production until the lowest quality land's marginal revenue equals the marginal cost of production. The land with highest production therefore generates the highest rent.

A German landowner Johann Heinrich von Thünen in the mid-19th century disagreed with Ricardo's theory on how rent is determined. Assuming all soils are uniform in productivity potential, Von Thunen argued that proximity to market is the most vital determinant of rent. Producers produce highly perishable commodities, such as milk and vegetables, on land in the immediate vicinity of the market city. Land use then transitions rapidly to grain production as one travels further away from central markets or ports. Before railroads revolutionized the transportation of goods, transportation of agricultural commodities required horses or other animals. Von Thunen drew a major conclusion from the farmer's dilemma that arose due to the highly inefficient modes of transportation. Highly perishable commodities aside, the further away from market a farmer lives, the larger the share of cargo devoted simply to animal feed. Hence, the share of cargo consumed is deemed the cost of transportation, and Von Thunen was able to derive a formula for calculating rental values:

$$Rent = Yield * (Price - Cost) - Yield * FreightRate * Distance$$

where FreightRate and Distance costs are smallest on land nearest to markets which equates to higher rental rates. Even in modern markets, cost basis formulas for elevators resemble Von Thunen's calculation above. Although different, both Ricardo and Von Thunen's formulas represent ways of calculating the profitability of a parcel of land.

3.2 - Supply and Demand Models

Ricardo's farmland price model resembles a supply and demand model, but he never introduces scarcity of land into his equation. Instead, he assumes that when commodity prices rise, producers bring an inferior class of soils into production. Recognizing that the supply of farmland was somewhat inelastic and much of the arable land in America was already being farmed, researchers in the 1960's began to analyze farmland values using simultaneous supply and demand models to explain farmland values and cash rent prices. Herdt and Cochrane (1966) link the divergence in trends of farmland prices and farm income to technological advances and supply pressure due to urban demand. Tweeten and Martin's (1966) five-equation model finds growing farm sizes and demand for nonfarm land use were the largest contributors to land price increases from 1923 to 1966. Floyd (1965) finds that government price-support programs, which restrict supply through either acreage or production limitations, result in a windfall gain for everyone in the form of increased land values. These models fit historical data quite well, yet Pope et al (1979) finds simultaneous equations hold very little predictive power when using current data.

3.3 - Net Present Value Models

Economists have used net present value models extensively in the past to value farmland. The present value model:

$$NPV = \sum_{t=1}^{T} \frac{Cash\ Flow_t}{(1+i)^t} - Initial\ Cash\ Investment$$

where cash flow represents the return in time t, and i equals the assumed discount rate.

Farmland as an asset generates income and therefore can be valued as the discounted sum of all future residual returns. In the most basic application, Melichar (1979) uses current returns to farmland, expected growth in returns to farmland, and a discount rate in a basic analysis of farmland values. However, Melichar overlooks how both costs and returns fluctuate through time, which results in imprecise estimates from the model. Phipps (1984) uses a Granger causality test to confirm the unidirectional relationship between farmland returns and farmland prices. That is, the residual returns to farmland affect the value of farmland, but the value of farmland has no effect on residual returns. Alston (1986) uses a present value model to examine the effects of inflation and real growth in net rental income on farmland prices. They find that “the direct evidence from U.S. data suggests that most of the growth of U.S. farmland prices can be accounted for by growth of rental income to land."

In the mid-1980s, advancements in econometrics allowed researchers to overcome two significant problems when trying to use time series analysis: nonstationarity of time series and incomplete data on information of market participants. Shiller (1984) uses these methods to analyze NYSE returns, which Falk (1991) replicates using Iowa land values. Both find inconsistencies compared to previous results from net present value models. Specifically, Falk finds that land values tend to overreact to changes in cash rent values; when cash rents rise, land values rise by too much, and land values fall by too much when cash rents drop.

While Falk (1991) argues against present value models, recent literature suggests these models still merit some reputability. Weersink et al (1999) uses a net present value model but includes an additional source of income: government payments. By allowing the discount rate to vary for both income sources, they find producers capitalize government payments into land values at a much smaller proportion than farm production returns. They propose uncertainty around the longevity of government programs as a potential explanation for this. Goodwin et al (2004) further this research using a present value model to examine how government payments are capitalized in to land values differently contingent on the program they are administered through. However, Goodwin et al (2003) questions the results of all previous literature, including his own, that uses present value models to evaluate farmland values. While the standard model assumes that land values are determined by long-run expected returns to land, expected returns are inherently unobservable. Furthermore, even if one fixes expected returns, the variation in government payments from year to year induces an identification problem unless one assumes individuals accurately predict the variation.

3.4 - Hedonic Models

Lancaster (1966) outlines hedonic pricing models in his consumer theory analysis of the economics of characteristics. Early research methods valued farmland based on each parcel's unique characteristics. However, hedonic pricing model posit farmland prices equal the sum of values derived from parcel characteristics. These characteristics may include soil quality, capital improvements, water supply, location to markets, and potential for future development (Bastian et al., 2002). These characteristics are inseparable and contribute to value in conjunction with each other. The heterogeneity across parcels differentiates the hedonic model from the classic supply and demand model, which assumes homogeneity of characteristics.

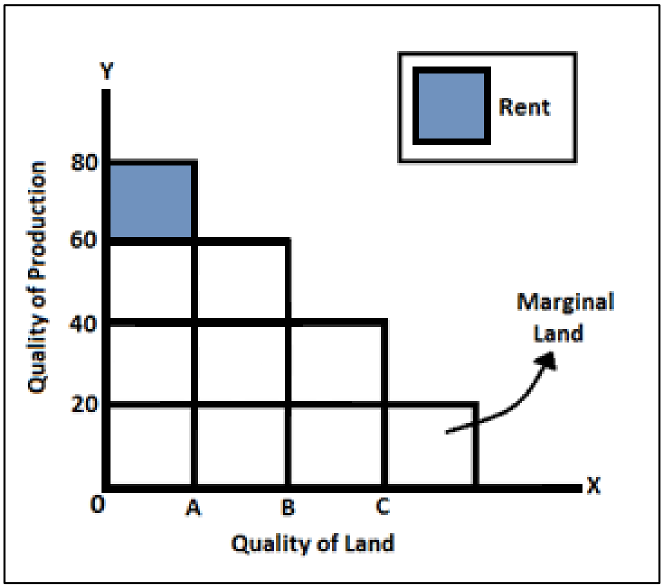
Articles that use hedonic price models to analyze farmland values (Chicoine, 1981; Veeman et al., 1993; Stewart & Libby, 1998; Barnard et al., 2001; Henderson & Moore, 2003; among others) outnumber those that analyze cash rent paid for farmland. These classic models may in fact do a poor job in their analysis of cash rents. Where proximity to urban areas and other long-term factors greatly affects farmland values, factors that affect potential income, such as soil productivity and commodity prices, have greater influence on cash rents (Hanson, 2012).

3.5 - Income Approach

Ricardo defined residual rent as the difference between revenue and costs; however, his approach focuses on soils as the main indicator of rents. The income approach explains rent as a function of residual rent, whereas the hedonic approach explains residual rent as a function of inherent parcel characteristics (Woodard, 2010). Featherstone and Baker (1988) derive residual rents from actual returns to corn and soybean farms in Tippecanoe County, Indiana from 1960 through 1985. For every dollar of residual rent in year *t,* cash rents increase \$0.08 in year *t+1* and \$0.60 in the long-run. Helmers (2004) explains why the inclusion of an inflation factor in the calculation of the real interest rate is critical to the derivation of the correct discount factor. Helmers finds that without this adjustment to the discount factor, the income approach attains a biased valuation of farmland.

3.6 - Figure

Figure 13:



CHAPTER 4 – MODEL AND DATA

4.1 – Theoretical Framework

Supply and demand determines the price paid for any particular parcel of land in the marketplace. When land is homogeneous, supply and demand models apply directly, however, land is heterogeneous. Therefore, this analysis uses a hedonic price model to quantify how the quantity and quality of a property's characteristics determine its price in the market. Hedonic models use a revealed price method to find the price of individual characteristics that constitute a good. The hedonic price model below:

$$R = R(z)$$

$$z = (z_1, z_2, \dots, z_{i)}$$

Where R is cash rent paid in a county, and z is a vector of characteristics that describe that county. A partial derivate of the hedonic function with respect to characteristic z_i, yields the price for characteristic z_i:

$$p_{z_i}(z_i) = \frac{\partial R}{\partial z_i}$$

Note, the marginal price function of z_i does not have to be a constant.

Because of the vast amount of quality real estate data available, most literature using spatial hedonic fixed effect models focuses on the real estate sector. These models reduce misspecification that is present due to omitted, time-invariant explanatory variables (Osland, 2013). More specifically, Can and Megbolugbe (1997) find that spatial hedonic fixed effects models reduce the extent of the prediction error, remove most of the systematic error, and produce better predictors of housing prices.

<u>Spatial Autocorrelation</u>

The First Law of Geography states: "Everything is related to everything else, but closer things more so" (Tobler, 1979). The concept Tobler references is spatial autocorrelation. Spatial autocorrelation, otherwise known as spatial dependence, is defined as the correlation between the distribution of a variable and its location (Anselin & Bera, 1998). Previous research focused on farmland valuation and farmland rental prices finds spatial correlation (Anselin, 1992; Du et al., 2007; Du et al., 2008; Huang et al., 2006; Soto, 2004).

Spatial autocorrelation and temporal autocorrelation are similar. However, temporal autocorrelation relates directionally one way, as events in period *t+1* cannot affect period *t*. Spatial autocorrelation relates in any proximity direction as different regions affect each other, therefore requiring an entirely different framework to account for spatial relationships.

Formally, if y_i and y_j are realizations of a random variable y, indexed by spatial locations, then we have spatial autocorrelation if:

$$Cov(y_{it}, y_{jt}) = E(y_{it}, y_{jt}) - E(y_{it})E(y_{jt}) \neq 0$$

where i and j are individual counties at time t, and y_{it} and y_{jt} are corresponding random variables.

Spatial autocorrelation can be both positive and negative, although negative autocorrelation is rare. Positive spatial autocorrelation implies the values of geographical neighbors tend to move together simultaneously. If present, spatial autocorrelation indicates the probability of a value taken on by any of the model's error term entries might affect the probability of a value taken on by one of the remaining error term entries. Failure to account for this relationship in the model violates the assumption of randomly distributed error terms.

Griffith (1987) ascertains the need for a measurement of spatial autocorrelation to index the nature and degree to which the data violate the fundamental statistical assumption, and describe the overall pattern across a geographic landscape. Moran (1950) developed the most commonly used measurement of spatial autocorrelation known as the Moran's-I test. The Moran's-I statistic for spatial autocorrelation is:

$$I = \frac{N}{\sum_{it}\sum_{jt}W} * \frac{\sum_{it}\sum_{jt}W(Y_{it} - \bar{Y})(Y_{jt} - \bar{Y})}{\sum_{it}(Y_{it} - \bar{Y})}$$

where N is the number of spatial units indexed by *i* and *j*, *Y* is the dependent variable, *t* is the index of time, and *W* is a weight matrix defining the relationship between observations. Moran's-I values range $-1<I<1$, where positive values indicate clustering, and negative values indicate dispersion. The null hypothesis is that there is no spatial autocorrelation, and the Moran's statistic is asymptotically standard normal, so is interpreted in the same way as a p-value (Viton, 2010).The greater in absolute value the Moran's-I value is, the stronger indication there is of spatial relationships in the data.

An equivalent of Moran's-I for panel data has yet to be developed for broad analysis. Baltagi et al (2003) propose lagrange multiplier (LM) tests to verify the presence of random effects and serial or cross-sectional correlation in panel data models. This analysis uses joint, marginal and conditional tests for all combinations of random effects and spatial correlation.

First, the joint hypothesis (Joint *LM*) of no spatial or serial error correlation and no random region effects is tested. The marginal LM test[1] (LM_1) for spatial error correlation assuming no serial correlation or random region effects is then used. Similarly, a marginal LM test for no serial correlation (LM_2) assuming no spatial error correlation or random region effects is used. Finally, one-dimensional conditional tests are used. The first (LM_λ) tests for no serial correlation assume the presence of spatial error correlation and random region effects. Likewise, the second (LM_σ) tests for zero random region effects assuming the presence of both serial and spatial error correlation.

Table 5 below presents the null and alternative hypotheses, along with results. P-values near zero for all tests reveal the presence of serial correlation, spatial error correlation, and random regional effects. This discovery reveals the use of a spatial model is required to ensure obtained estimators are efficient.

Weight Matrix

A spatial weight matrix *W* is defined as the formal expression of spatial relationships among observations (Anselin & Bera, 1998). The weight matrix is an NxN positive matrix in which the rows and columns correspond to the cross-sectional observations (Anselin et al., 2008). Weight matrices vary in their structure and format. The most basic weight matrix is a binary matrix where a value of 1 represents a neighbor, with 0 for everyone else. The diagonals each equal 0

[1] This is the original marginal LM test developed by Anselin (1988).

as well, as units cannot be neighbors with themselves. One feature of neighbors is that they do not vary over time. Unless the weights are based on a formal theoretical model for social or spatial interaction, their specifications are often *ad hoc* (Anselin et al., 2008).

This study uses a great circle distance weight matrix at the smallest distance possible while simultaneously not creating "island" counties that have no neighbors. No known previous literature models information flow between counties about cash rental values and other agricultural information, but the general consensus is that information flow does exist. For example, a producer will not pay two vastly different rental rates for a uniform parcel of farmland divided in half by an arbitrary county border, *ceteris peribus*.

Spatial software such as *Geoda* expedites the neighbor identification process. In the data used in this analysis, *Geoda* identifies 90 kilometers as the minimum distance that creates zero island counties. The resulting weight matrix takes the form:

$$w_{ij}^{*} = \begin{cases} 0\ if\ i = j \\ 1/d_{ij}^{2}\ if\ d_{ij} \leq 90 \\ 0\ if\ d_{ij} > 90 \end{cases}$$

and

$$\mathrm{W} = w_{ij}^{*} \Big/ \sum_{j} w_{ij}^{*}$$

Where w_{ij}^{*} is an element of the unstandardized weight matrix, w_{ij} is an element of the row-standardized weight matrix W, and d_{ij} is the great circle distance between centroids of region *i* and *j*.[2]

The weight matrix W must be row standardized due to the variation in number of neighbors by county. Row standardization subjects each county to the same total spatial influence from surrounding counties, regardless of the number of neighbors they have. The process of row standardization involves dividing each neighbor weight for a specific feature by the sum of all neighbor weights for that feature. Each row standardized weight can then be interpreted as the fraction of all spatial influence on $county_i$ attributable to $county_j$. The resulting weight matrix W applies not only to cross-sectional data, but to panel data as well, given the spatial attributes remain constant through time. Using the subscript to designate the matrix dimension, with W_N as the weights for the cross-sectional dimension, the full NT ×NT weights matrix then becomes:

$$W = I_T \otimes W_N$$

with N as the number of observations in the cross-sectional matrix, T as the number of periods, and I_T as an identity matrix of dimension T (Anselin et al., 2008).

While time series analysis uses time lag operators to incorporate information about neighbor observations, spatial panel models use spatial lags. The need for spatial lags arises from the irregular nature of spatial relationships in which the number of neighbors may vary drastically across a dataset. In essence, a spatial lag operator constructs a new variable that consists of

[2] No time dimension *t* is included as the weight matrix W is constant through time.

the weighted average of the neighboring observations, with the weights as specified in W (Anselin et al., 2008). Spatial lags therefore can be applied to the dependent variable, the independent variables, or the error term to control for spatial relationships.

<u>Spatial Hausman Test</u>

Previous literature progressed from supply and demand models, to net present value models, to hedonic models most recently. These models do not explicitly account for the relationships that exist when neighboring counties affect each other's rents. Therefore, a spatial model is required to account for these relationships. Spatial panel data offers the ability to isolate specific effects that may be due to spatial or temporal attributes.

As with classic panel regression models, spatial panel models are either random or fixed. A spatial Hausman test is employed to determine whether a random or fixed effect estimator should be used. This test determines between two estimators differing in efficiency. The alternative hypothesis of the spatial Hausman test finds misspecification the two estimators yield divergent results (Pace, 2008). The Hausman test statistic takes the form

$$H = NT(\hat{\theta}_{FGLS} - \hat{\theta}_W)^T(\hat{\Sigma}_W - \hat{\Sigma}_{FGLS})^{-1}(\hat{\theta}_{FGLS} - \hat{\theta}_W)$$

where $\hat{\theta}_{FGLS}$ and $\hat{\theta}_W$ are, respectively, the spatial GLS and within estimators, and $\hat{\Sigma}_W$ and $\hat{\Sigma}_{FGLS}$ the corresponding estimates of the coefficients' variance covariance matrices. H is asymptotically distributed X^2 with k degrees of freedom where k is the number of regressors in the model (Millo & Piras, 2012).

In the case of this analysis, the spatial Hausman test determines whether the data support a random or fixed effects model.

$$H_0 : X^2 \geq 0.05$$
$$H_{a:}\ X^2 < 0.05$$

where an insignificant p-value implies the random effects model is safe to use. Table 6 below displays the X^2 statistics from the spatial Hausman tests on the different regressions. Each regression returns a statistically significant p-value, allowing us to reject the null hypothesis in favor of the spatial fixed effects model.

4.2 – Spatial Autoregressive Fixed Effect Model

Spatial lag and spatial error models are the two most commonly used spatial-temporal models. Three different types of spatial interaction effects can be distinguished in these models: endogenous interaction effects among the dependent variable, exogenous interaction effects among the independent variables over space, and interaction effects among the error terms over space (Elhorst, 2011). Spatial error models control for interaction effects among the error terms over space, while spatial lag models control for the other two. When there are no strong *a priori* theoretical reasons to believe that interdependences between spatial units arises either due to the spatial lags of the dependent variables or due to spatially autoregressive error terms, the standard approach is to model the system with both effects included (Anselin, 2002). The spatial autoregressive (SARAR) fixed effect model combines the two models and controls for interaction effects among the error terms over space and endogenous interaction effects among the dependent variable.

First, consider a general static panel model that includes a spatial lag of the dependent variable and spatial autoregressive disturbances:

$$y = \lambda(I_T \otimes \mathrm{W})y + X\beta + u$$

where y is an *NT* x 1 vector of observations on the dependent variable, X is a *NT* x *k* matrix of observations on the non-stochastic exogenous regressors, I_T an identity matrix of dimension *T*, W is the NT x NT spatial weights matrix of known constants whose diagonal elements are set to zero, and λ the corresponding spatial parameter. The disturbance vector u is the sum of two terms

$$u = (\iota_T \otimes I_N)\mu + \varepsilon$$

where ι_T is a T × 1 vector of ones, I_N an N x N identity matrix, μ is a vector of time invariant individual specific effects (not spatially autocorrelated), and ε a vector of spatially autocorrelated innovations. To further allow innovations to be correlated over time, the innovations vector follows an error component structure

$$\varepsilon = (\iota_T \otimes I_N)\mu + v$$

where ρ is the corresponding spatial autoregressive parameter, μ is the vector of cross-sectional specific effects, v a vector of innovations that vary both over cross-sectional units and time periods, ι_T is a vector of ones and I_N an N × N identity matrix

As in the classical panel data literature, the individual effects can be treated as fixed or random. Fixed effect models control for all time-invariant latent variables that influence the dependent variable, whether these variables are known or unknown. The spatial Hausman test applied to the models in this analysis determined the spatial fixed effect model provided the most efficient estimates.

A SARAR fixed effects model can be written in stacked form as

$$y_{it} = \lambda(I_T \otimes \mathrm{W})y_{it} + (\iota_T \otimes I_N)\mu_{it} + X\beta + u_{it}$$

The presence of the spatial lag introduces a form of endogeneity that violates the assumption of standard regression models (i.e., the regressors are uncorrelated with the error term). Elhorst (2003) transforms the variables in the equation above by eliminating the time invariant individual effects and uses the transformed variables to maximize the likelihood function. The transformation is obtained by subtracting the average for each cross-section over time. As a consequence, the fixed effects and the constant term (as well as other variables that do not vary over time) are wiped out from the model. The error term estimation strategy from the cross-sectional spatial error model is then extended to the panel context.

$$u_{it} = \rho(\mathrm{I}_T \otimes \mathrm{W})u_{it} + \varepsilon$$

The resulting model of cash rents for county *i* at time *t* is:

$$CashRent_{it} = \rho W(CashRent_{it}) + \beta_0 + \beta_1 NetValue_{it} + \beta_2 ExpectedCornRevenue_{it} + \beta_3 ExpectedSoybeanRevenue_{it} + u_{it} + z_t + s_i$$

where $\rho W(CashRent_{it})$ is a spatial lag of the dependent variable in county *i* at time *t,* $NetValue_{it}$ is the one, three, and five year lagged moving averages of net value from crop insurance in county *i* at time *t,* $ExpectedCornRevenue_{it}$ is the revenue expected from one acre of production of corn in county *i* at time *t,* $ExpectedSoybeanRevenue_{it}$ is the expected revenue from one acre of production of soybeans in county *i* at time t, z_t is a 1 x T matrix of the year fixed effect estimates, and s_i is a 1 x N matrix of the county fixed effect estimates.

Figure 14 below displays the map of the county fixed effect estimates. The county fixed effects matrix s_i can be treated as a dependent variable in a cross-sectional regression to determine the impacts that time invariant variables have on cash rents. As figure 14 shows, spatial relationships exist among the county fixed effect estimates. To account for these relationships, a cross-sectional version of the previously defined SARAR model is used. The resulting cross-sectional model is:

$$FEestimates_i = \rho W(FEestimates_i) + \beta_0 + \beta_1 Soil_i + \beta_2 CornStDev_i + \beta_3 SoybeanStDev_i + \beta_4 GDD_i + u_{it}$$

where $\rho W(FEestimates_i)$ is a spatial lag of the fixed effect estimates, $Soil_i$ is a productivity measure of soils in county *i*, $CornStDev_i$ is the standard deviation of detrended corn yields in county *i*, $SoybeanStDev_i$ is the standard deviation of detrended soybean yields in county *i*, GDD_i is the average GDDs in county *i*, and u_i is the previously defined SARAR error term that controls for spatial error autocorrelation.

4.3 – Data

Cash rent paid for non-irrigated land is the dependent variable used in this thesis. The National Agricultural Statistics Service (NASS) conducts hundreds of surveys annually, one of which collects data on cash rent paid for non-irrigated land. NASS compiles these data using surveys administered on farms and ranches that rent land on a cash basis. Excluded from the cash rent value is land rented for a share of the crop, rent determined by animal production, land rented free of charge, or land that includes buildings such as barns.

NASS records provide panel data of cash rental values for the period 2008-2016. Panel data are ideal for this study, as Elhorst (2011) states panel data are generally more informative and contain more variation and less collinearity among the variables. A regulation change in 2014 required NASS to survey producers about land values on a biannual basis, which created a gap in the data between 2014 and 2016.[3]

One limitation in the analysis arises from an unbalanced panel due to incomplete data. Due to the spatial nature of the question examined in this thesis, analysis of only counties with a complete eight-year rent data results in an "island" problem. Islands occur in spatial models when individuals possess zero neighbors. Some spatial computational routines cannot be completed when islands exist in the data, and most econometricians consider it best practice to avoid islands in spatial models. To circumvent this error, spatially interpolated values are used in lieu of missing values to create an artificially balanced panel data set. Table 7 below breaks

3. For comparison in the analysis, 2015 rental values are imputed using a simple average of 2014 and 2016 rental values. Small differences exist in coefficient magnitudes when comparing regression results that include and exclude the 2015 imputed cash rents.

out imputed missing values by state. LeSage and Pace (2004) suggest replacing the unobserved data with expected values conditional on the observed data. The spatial interpolation used the simple average of the five nearest neighbor counties in that year to complete the dataset.[4] This represents a simplified method of kriging, which is an optimal linear prediction method applied to random processes in space.

After missing values were imputed, complete data existed for 985 of the 1,017 counties in the Midwest. Figure 16 below displays cash rent values for those 985 counties in 2016. Highest rent values are located in the counties in southern Minnesota through Iowa and into central Illinois. Figure 17 below displays a map of detrended yields of corn, which bears a strong resemblance to the graph of cash rent. One could argue in favor of Ricardo's cash rent theory based on these two graphs alone.

An additional concern relates to the construction of the aggregated data set employed in this analysis. Spatial analyses often use arbitrary regions such as census tracts or counties. Statistical literature often criticizes this method as yielding invalid inference, the so-called *ecological fallacy* problem (Anselin, 2003). Broadly, the *ecological fallacy* problem refers to the inconsistency that arises from micro-interpretations based off macro-analysis. In the context of this analysis, data are aggregated based off arbitrary county lines and results are then interpreted as producer-level. Different aggregation methods applied to data help determine the sensitivity of the results to the *ecological fallacy* problem. This is impractical in the case of

[4] Boehmke and Schilling (2015) recommend the Expectation Maximization (EM) approach to address the missing data problem in spatial panel models. That approach applied to this analysis produced inconsistent and illogical rent values, which resulted in inefficient estimators.

this analysis though as data on multiple variables were collected in an aggregated form. Therefore, this thesis interprets macro-analysis results as producer-level with caution.

Explanatory Variables

The variable of interest in this thesis is the net value of crop insurance to the producer on a per acre basis. The net value of crop insurance variable is calculated as

$$Net\ Value/Acre_{it} = \frac{(Indemnity_{it} +\ Subsidy_{it} -\ Premium_{it})}{Acres_{it}}$$

where each net value per acre equals the ratio in each county *i* at time *t,* of indemnity plus subsidy minus premium, all divided by acres. RMA's Summary of Business data contain county level crop insurance premiums, indemnities, and subsidies from the 1980's to current. This analysis only references RMA Summary of Business data from 1995 through 2016, as premium rating, products offered, and subsidy rates changed drastically after the 1994 Act. As illustrated by Figure 15 and the yearly net value maps in Appendix B, net values vary widely across space and time, but also cluster spatially. Analysis of this variation reveals the effect of net value of crop insurance on rental values.

Previous agricultural land value literature uses a plethora of different variables in hedonic price models (Palmquist & Danielson, 1989; Chicoine, 1989; Drescher et al., 2001; Bastian et al., 2002; Patton & McErlean, 2003; Huang et al, 2006; Guiling et al., 2007; Baylis et al., 2011). This thesis includes several of these variables for analysis and comparison against previous literature. These variables are classified as either time variant or time invariant. As previously discussed, the fixed effect models by design cannot include time invariant variables. The time invariant variables included in this analysis are used in robustness checks with random effects models and in cross-sectional regressions.

Time Variant Variables

Farmland values are established by an array of factors, both related to production of farm commodities and not. However, producers establish cash rents for farmland mainly off factors that influence income expectations. To control for income expectations, expected revenue from corn and soybeans are calculated from trend yields and crop insurance harvest prices from the prior growing season. Crop insurance harvest prices provide the best commodity price estimate for expected revenues the following year given cash rents are often negotiated in the fall (Woodard, 2012). Expected revenue therefore equals the harvest price multiplied times the trend yield for both corn and soybeans.

Time Invariant Variables

Soil productivity is widely recognized as an important driver of rental values. Soil productivity measures how soil profiles either promote or impede yield potential. States in the Midwest often use indexes unique to individual states, with no conventional conversion method to standardize across space. For example, Illinois uses a Productivity Index where values range from 47 to 147, while Iowa uses a Corn Suitability Index that ranges from 0 to 100. While both score on a 100-point scale, soil attributes are valued differently in each case. However, the Natural Resources Conservation Service (NRCS) derived the National Commodity Crop Productivity Index (NCCPI), which is a county level measure of soil productivity. The NCCPI values the natural relationships of soil, landscape, and climate factors, and the responsiveness of commodity crops to those factors on a 0 to 1 scale. For the purpose of this study, the NCCPI remains static through time, although literature suggests erosion affects soil productivity through time (Williams et al., 1983)

Trend yields provide an expected production value for any given county, which affects expected revenue, but the variance of that yield is also an important consideration. Barry et al (2000) show cash rental rates include a risk premium based upon the historical variance of yields. Under cash rent arrangements, producers bear 100% of the yield risk, versus sharecropping arrangements, where yield risk is divided proportionally between landlord and producer. This thesis employs a standard deviation of yield to control for the effect of yield variance on cash rental rates.

Detrended yields are used to calculate standard deviations for corn and soybeans. Detrended yield values are used to account for the increase in yields through time for corn and soybeans. Uncorrected yield data results in an average yield that is biased downwards and standard deviation of yield that is biased upwards. The detrended yield calculation for each county *i* at time *t* is:

$$detrendedyield_{it} = yield_{it} + \beta_i * (2016 - t)$$

where β_i is the slope coefficient of yields for county *i* for the period 1980 through 2016, and *t* is the corresponding year of the yield value. $detrendedyield_i$ is a simple average of detrended yield values for county *i*. We calculate standard deviation of detrended yields σ_i with the detrended yield values.

Weather is another important factor in crop production and therefore impacts cash rents. Weather is the day-to-day variability of solar radiation, air temperature, humidity, and precipitation across the landscape (Hollinger, 2009). These are all key atmospheric variables that affect crop yields. Climate is the long-term average of these variables over a crop's growing season. In the absence of weather extremes, climate determines the realized yields for any given county. To control for the effect of different climate patterns on cash rents in the Midwest, this analysis uses a measurement of heat units.

Physiologically, below or above certain temperatures, crops cease growth development. To quantify the amount of heat available to crops, a measure of heat units, growing degree days (GDDs), is used. Using county level PRISM weather data, GDDs are calculated as

$$GDDs = \sum \frac{(T_{max} - T_{\min})}{2} - T_{\mathrm{base}}$$

where T_{max} is the daily maximum air temperature, T_{min} is the daily minimum air temperature, T_{base} is the temperature below which crop growth ceases, and the daily *GDDs* are constrained to greater than or equal to zero. While base temperatures vary by crop (Yang et al., 1995), the most common base temperature used in GDD calculations, and by this analysis, is 50°F. GDDs in this analysis are the county average from 2008-2016.

Table 9 below displays the relationships among all variables. High collinearity exists among many of the variables, especially the net values of crop insurance, which complicates the interpretation of this table. However, interesting insights are garnered from the net value correlations. First, the correlation between rent and the smaller net values ranges from none to very weak. This result occurs due to the spatial variation of large net value payments in the short run. A weak negative correlation emerges though as net values are averaged over a longer period. Second, each net value variable is strongly correlated with the others, other than the one-year net value. The one-year net value exhibits only a moderate correlation with other net value variables, implying net values from one year of data are only slightly related to long-term averages.

4.4 – Tables and Figures

Table 5:

Lagrange Multiplier Tests for Random Effects and Spatial Autocorrelation			
Number of Years of Average Previous Net Value	**1 Year**	**3 Year**	**5 Year**
Joint LM H_0: $\lambda = \rho = \sigma_\mu^2 = 0$ H_a: $\lambda = \rho = \sigma_\mu^2 \neq 0$	37,052 (0.00)	37,183 (0.00)	37,227 (0.00)
$\boldsymbol{LM_1}$ H_0: $\sigma_\mu^2 = 0$ (assuming $\lambda = \rho = 0$) H_a: $\sigma_\mu^2 \neq 0$ (assuming $\lambda = \rho = 0$)	127.91 (0.00)	127.42 (0.00)	127.54 (0.00)
$\boldsymbol{LM_2}$ H_0: $\lambda = 0$ (assuming $\rho = \sigma_\mu^2 = 0$) H_a: $\lambda \neq 0$ (assuming $\rho = \sigma_\mu^2 = 0$)	143.85 (0.00)	144.73 (0.00)	144.78 (0.00)
$\boldsymbol{LM_\lambda}$ H_0: $\lambda = 0$ (assuming $\sigma_\mu^2 = \rho \neq 0$) H_a: $\lambda \neq 0$ (assuming $\sigma_\mu^2 = \rho \neq 0$)	67.68 (0.00)	67.85 (0.00)	68.18 (0.00)
$\boldsymbol{LM_\sigma}$ H_0: $\sigma = 0$ (assuming $\lambda = \rho \neq 0$) H_a: $\sigma \neq 0$ (assuming $\lambda = \rho \neq 0$)	126.89 (0.00)	126.41 (0.00)	126.52 (0.00)
p-values in parentheses			

Table 6:

Hausman Test for Spatial Models		
Number of Years of Average Previous Net Value	Chi-Squared	p-value
1 Year	243.32	0.00
3 Year	266.14	0.00
5 Year	313.3	0.00

Table 7:

	Potential	NASS Total	Missing Values	% missing
All 985 Counties	8865	8013	852	9.61%
Illinois	873	819	54	6.19%
Indiana	828	726	102	12.32%
Iowa	891	889	2	0.22%
Kansas	837	743	94	11.23%
Michigan	621	491	130	20.93%
Minnesota	747	708	39	5.22%
Missouri	900	784	116	12.89%
Nebraska	684	597	87	12.72%
North Dakota	477	469	8	1.68%
Ohio	774	681	93	12.02%
South Dakota	594	542	52	8.75%
Wisconsin	630	564	66	10.48%

Figure 14:

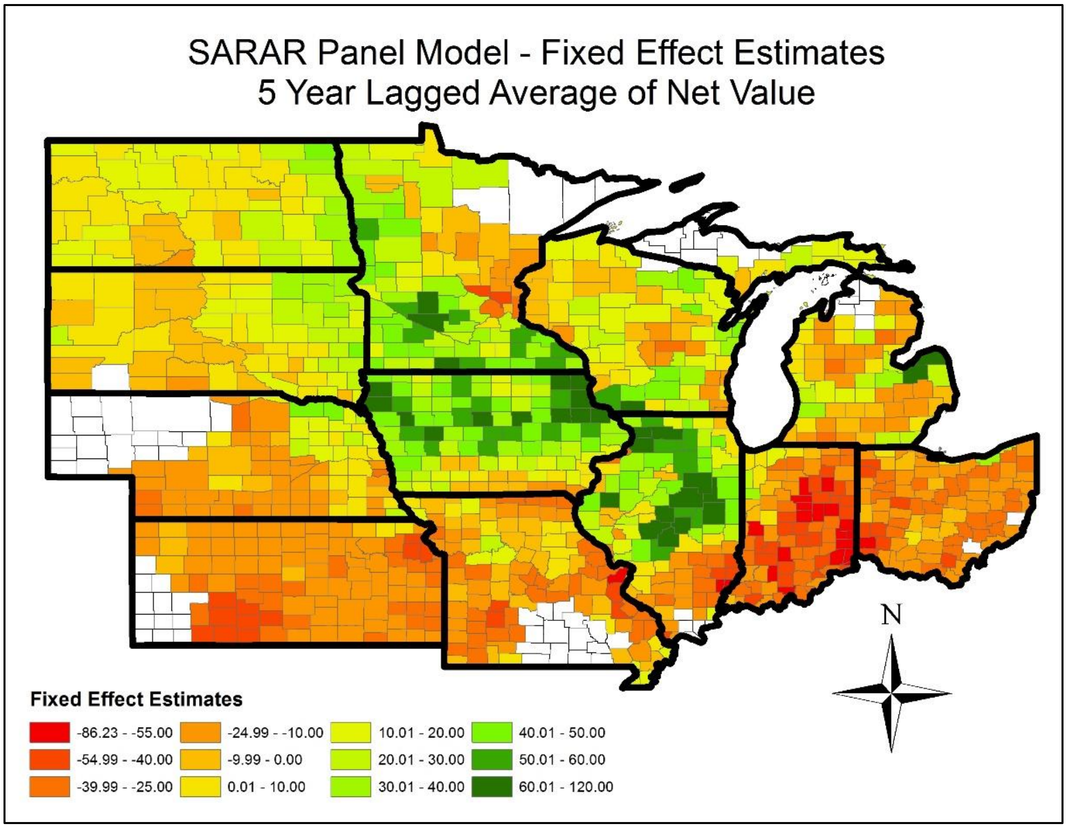


Figure 15:

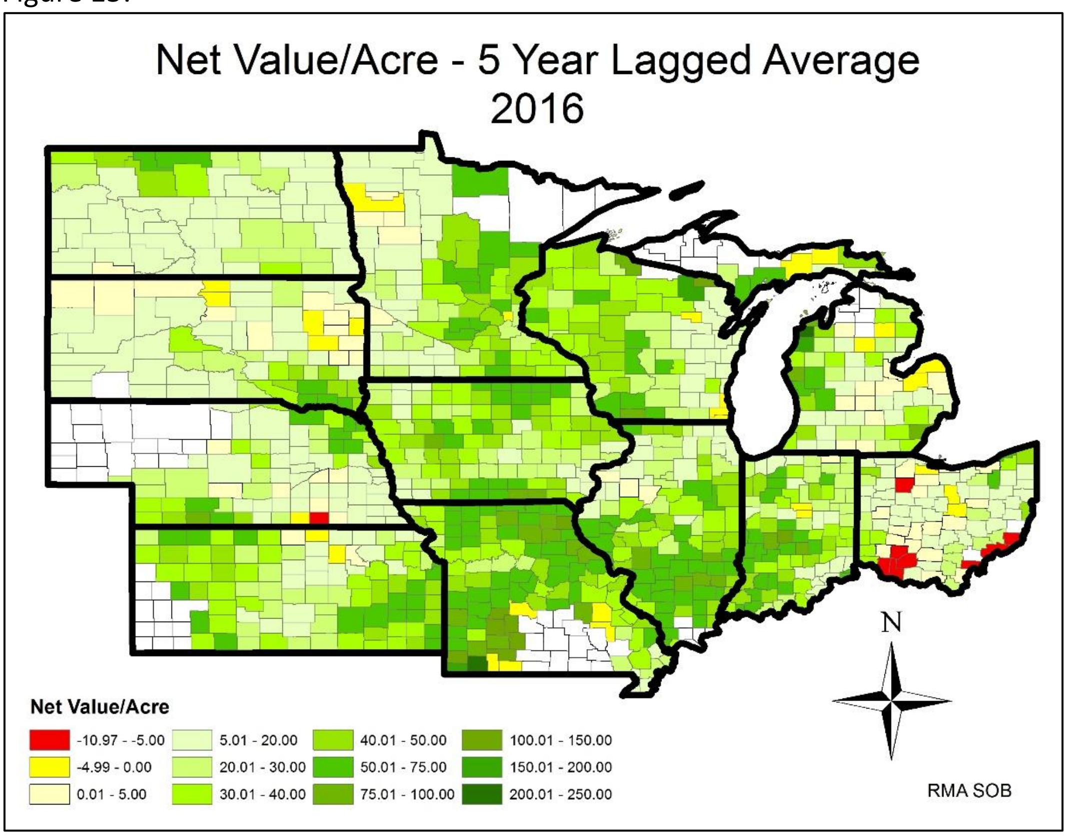


Figure 16:

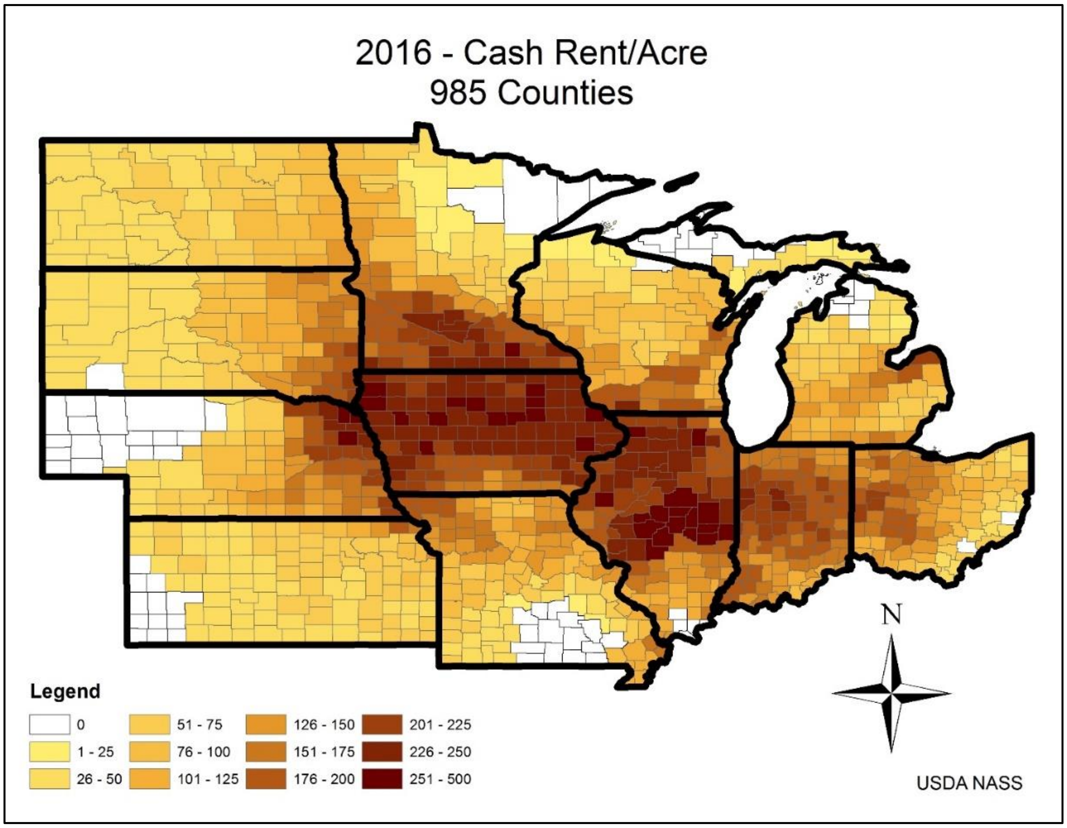


Figure 17:

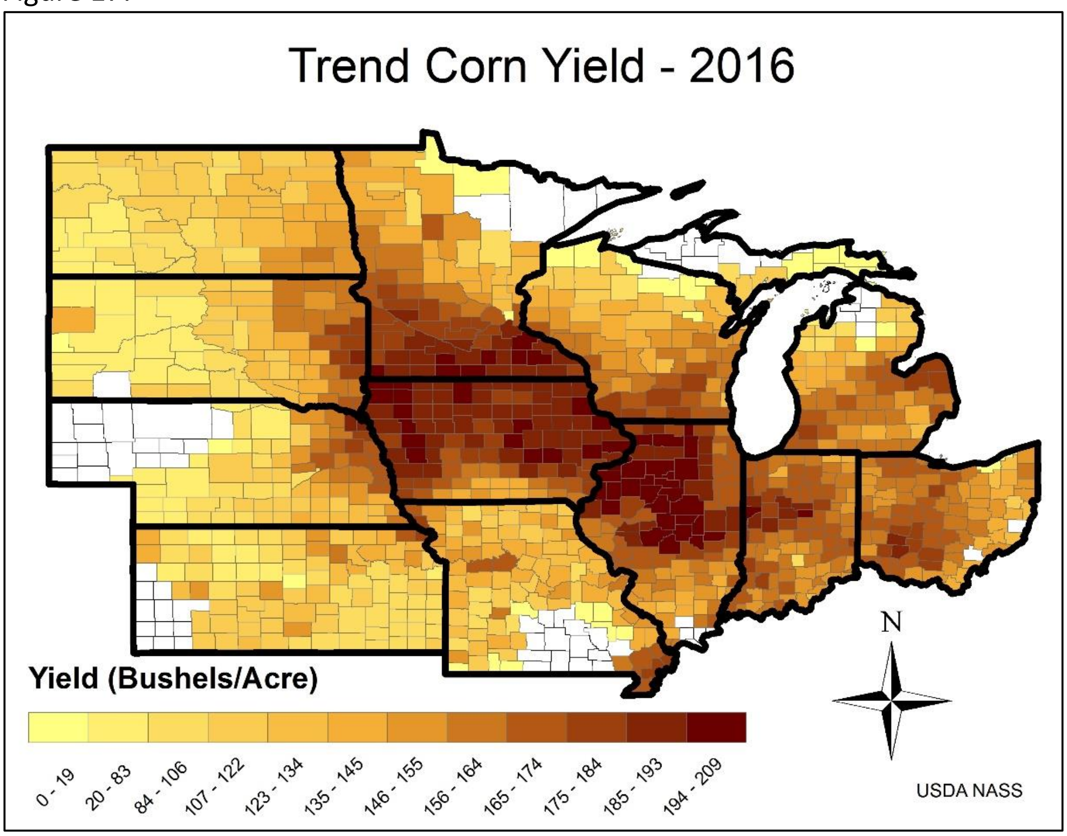


Table 8:

Variable	Mean	StDev	Min	Max
RENT	112.98	66.16	7.9	385
1 YEAR NV	22.62	54.43	-45.13	705.37
3 YEAR NV	18.06	29.58	-39.34	360.96
5 YEAR NV	16.15	22.17	-30.48	282.28
EXPECTED CORN REVENUE	684.87	272.67	165.53	1585.22
EXPECTED SOY REVENUE	462.31	184.45	145.58	2293.11
GDD	3139.3	707.9	1557.9	5012.7
SOIL	0.505	0.178	0.114	0.912
CORN YIELD AVE	148.28	40.86	43.22	220.07
CORN YIELD STDEV	19.17	6.98	7.49	49.15
SOY YIELD AVE	43.15	14.71	15.79	70.52
SOY YIELD STDEV	5.48	2.19	1.75	12.58

Table 9:

Correlation Matrix of Variables

	RENT	SOIL	CORN REVENUE	SOYBEAN REVENUE	StDev - CORN	StDev- SOYBEANS	GDD	NET VALUE - 1 YEAR	NET VALUE - 3 YEAR	NET VALUE - 5 YEAR
RENT	1	0.79	0.54	0.58	0.09	0.02	0.09	0.00	-0.01	-0.04
SOIL	0.79	1	0.39	0.42	0.20	0.20	0.33	-0.01	-0.07	-0.10
CORN REVENUE	0.54	0.39	1	0.81	-0.09	-0.02	0.02	0.22	0.01	-0.06
SOYBEAN REVENUE	0.58	0.42	0.81	1	-0.04	0.01	0.09	0.20	0.08	-0.04
StDev - CORN	0.09	0.20	-0.09	-0.04	1	0.49	0.52	0.16	0.19	0.22
StDev- SOYBEANS	0.02	0.20	-0.02	0.01	0.49	1	0.34	0.04	0.05	0.05
GDD	0.09	0.33	0.02	0.09	0.52	0.34	1	0.09	0.09	0.08
NET VALUE - 1 YEAR	0.00	-0.01	0.22	0.20	0.16	0.04	0.09	1	0.67	0.60
NET VALUE - 3 YEAR	-0.01	-0.07	0.01	0.08	0.19	0.05	0.09	0.67	1	0.87
NET VALUE - 5 YEAR	-0.04	-0.10	-0.06	-0.04	0.22	0.05	0.08	0.60	0.87	1

CHAPTER 5 - RESULTS

Table 10 below displays results from the SARAR fixed effects model. Cash rent in each county is the dependent variable against which all independent variables are regressed. Results confirm expected coefficient signs for all statistically significant variables. Analogous to Ifft, Wu, and Kuethe's (2014) results, the consistency of net value that producers receive influences both the coefficient magnitude and significance level.

The results in this analysis are interpreted with caution. The endogeneity remaining in the model and the ecological fallacy problem, which warns against the interpretation of aggregate data at the producer level, complicate the interpretation of results. Because producers determine cash rents and crop insurance coverage in a joint evaluation with other production decisions, even using a spatial panel fixed effect model likely does not eliminate all endogeneity.

Table 10 shows there is strong evidence that crop insurance affects cash rents. As the moving averages over which net value is calculated increase in length, the coefficients both grow and migrate from statistical insignificance to statistical significance. The one-year lag and three-year lag of net value are positive but statistically insignificant, while net value is statistically significant at the 95% confidence level for the five-year lagged average of net value.

Interpreting the coefficients of net value, the consistency of receiving net value from crop insurance has a significant impact on the degree to which producers factor the net value into cash rents. The one-year and three-year lagged averages of net value reveals that producers who receive consistent net value from crop insurance over a period of one to three years do not factor a statistically significant amount of net value into cash rents. However, as the consistency of net value increases, producers do factor a statistically significant proportion into cash rents. A producer who receives one dollar of net value from crop insurance consistently for five years factors 0.96 cents directly into cash rents, after all other adjustments.

These results agree with Langemeier (2013). However, they contrast previous analysis of government payments to producers. Van Herck *et al*. (2013) found that producers factor up to $0.25 of each additional dollar of direct payments from the government into cash rents. The results from this thesis indicate that producers only factor $0.01 of every dollar of net value from crop insurance into cash rents.

One concern with the interpretation of the net value coefficients is that some counties consistently experienced negative net values of crop insurance. Figure 15 shows the five-year lagged average of net values in 2016, and multiplying the coefficients found in the regressions below times the five-year lagged average of net value, we find that, *ceteris peribus*, some counties paid less for cash rents due to crop insurance. However, this interpretation is illogical. Counties supposedly paying less for cash rents feasibly stems from endogeneity that remains in the model.

Additionally, the economic significance of the net value results is difficult to directly assess. The average rent in 2016 for the 985 counties in this analysis was $112.98. Using the largest five-year average net value of $282.28, cash rents were only $2.70 higher per acre due to crop insurance in that county. The $16.15 average five-year lagged average of net value equates to cash rents per acre that are higher by $0.16 due to crop insurance. For comparison, the 2016 crop insurance base price for corn was $3.86 per bushel.

Coefficients for expected revenue from corn were both positive and statistically significant at the 99.9% confidence level, regardless of the length over which net value was calculated. This affirms income as a significant factor considered when producers and farmland owners negotiate cash rents. While not directly comparable, producers factor a larger proportion of expected corn revenue into cash rents in comparison to the five-year lagged average of net value. However, these variables are difficult to disentangle, as producers perhaps factor net value from crop insurance into expected revenue from corn.

Expected revenue from soybeans was positive as well, but statistically insignificant. This potentially results from the strong degree of correlation between expected revenue from corn and soybeans confounding the results. Table 9 shows a correlation coefficient of 0.81 between these variables. The additional results tables (Tables 13-18), most often, either expected revenue from corn or expected revenue from soybeans has a statistically significant impact on cash rents, but rarely both.

Table 10 also contains the spatial coefficients from each regression. The spatial error coefficients reflect the latent spatial dependence in the data. These coefficients measure the average influence on observations by their neighboring observations. The positive and highly significant spatial lag coefficients signify that cash rents of each county positively influence cash rents in neighboring counties. Practically, cash rents paid for farmland near county borders are highly influenced by cash rents paid for nearby farmland, regardless of which county that farmland is located within.

Table 11 displays the marginal effects from each regression. Direct effects are the average effect of changes to an explanatory variable in $county_i$ on cash rent values in each of $county_i$'s neighbors. For example, if the average five-year net value of crop insurance increased by $1.00 in $county_i$, cash rents in $county_i$'s neighbors, on average, would increase $0.018. Conversely, indirect effects are the average impact on cash rents in $county_i$ if all values for an explanatory variable increased by one in each of $county_i$'s neighbors. Therefore, an increase of net value by $1.00 in each of $county_i$'s neighbors would raise cash rents in $county_i$ by $0.083.

Similar to the point estimate coefficients, the only statistically significant marginal effects for net value are those averaged over five years. Marginal effects for expected corn revenue are each statistically significant while none are for expected soybean revenue. The magnitude of the indirect effects tends to be larger than the magnitude of the direct effects. This indicates cash rent increases in $county_i$'s neighbor counties due to consistent net value has a larger effect than the effect on $county_i$'s neighbors if $county_i$ experienced an additional dollar in consistent net value.

The remaining independent variables are time invariant and so can only be regressed against the fixed effect estimates from the SARAR fixed effect model. Table 12 displays the results from these cross-sectional regressions below. Soil has a positive and statistically significant impact on cash rents in each regression. Producers therefore pay significantly higher cash rents for soils with higher productivity indexes. Standard deviation of yield for corn is insignificant, but for soybeans was statistically significant and negative. This affirms that producers significantly discount farmland where soybean yields are riskier because they bear all risk in a cash rental agreement.

To measure the effect of weather, average growing degree days (GDDs) is included in the time invariant variables, as long term weather patterns are most often assumed when rents are established. The results found GDDs have a statistically significant and negative impact on cash rents. This reflects the fact that excessive or minimal amounts of GDDs can harm plant growth, which results in lower yields, and is therefore factored into rents.

For robustness checks, a SARAR random effects model and non-spatial panel model are applied to the data in this analysis. Tables 13 and 14 report the results from the robustness checks. Net value coefficients in each of the three regions follow a familiar pattern to results from the SARAR panel fixed effects model.

Consistency of net value again determines the magnitude and statistical significance of coefficients. In both the SARAR fixed and random effects models, only the five-year average was statistically significant, reaffirming the length over which net value is measured is an important factor to consider. In the SARAR random effects model, the net value coefficients are very similar to the SARAR fixed effect model. The five-year net value coefficient was 0.0096 in the SARAR fixed effect model compared to 0.0101 in the SARAR random effects model.

The non-spatial fixed effects model found net value coefficients significantly larger in magnitude though. The three and five-year moving averages of net value were both statistically significant and 0.1155 and 0.3325, respectively. This represents a significant increase in magnitude in comparison to the SARAR fixed effects model. Not accounting for spatial relationships in the data would therefore results in a vastly different conclusion in this analysis. Again, these models are inefficient in comparison to the SARAR fixed effects model, as the LM and Spatial Hausman tests found, and are only reported for comparison.

Because producer experiences with crop insurance are highly related within regions, additional robustness checks are included in this analysis. First, a SARAR fixed effect model is used to analyze the three ERS regions in this analysis (Corn Belt, Lake States, and Northern Plains) separately. Additionally, because the data for Iowa are nearly 100% complete, an additional SARAR fixed effect model is used on Iowa alone as a robustness check.

Tables 15-17 report the results from the regional regressions below. The results from the Northern Plains closely resemble the results from all 985 counties. Expected corn revenue has a positive and statistically significant effect on cash rents while expected soybean revenue does not. Net value also has a positive and statistically significant impact on cash rents, but only when a five-year moving average is used. The magnitude of the five-year net value coefficient is 0.0298, which is slightly larger than the results from the complete sample.

Similar to the results from the Northern Plains regressions, the coefficients for expected revenue in the Lake States from corn were positive and statistically significant for corn, but statistically insignificant with mixed signs for soybeans. Net value was negative in the one-year moving average, but statistically insignificant. This result may reflect the volatility in payments from year to year. The three and five-year net values were statistically significant and comparable in magnitude to the five-year coefficient from the Northern Plains.

The results from the Corn Belt regressions find that expected revenue from both corn and soybeans has a positive and statistically significant impact on cash rents. The net value coefficients are positive, but statistically insignificant in each regression. This region had the most complete data set of all three regions in this analysis, which may indicate RMA is able to rate this region more accurately.

The results from the Iowa regression appear to reaffirm this, as coefficients for expected revenue from corn and soybeans are similar to the previous regressions, but the net value coefficients are not. In the Iowa analysis, all net value coefficients are positive, but only the one-year moving average is statistically significant. However, the previous regressions show that the moving averages greater in length most accurately reflect the true nature of the situation.

5.1 – Tables and Figures

Table 10:

SARAR Fixed Effects Panel Model Midwest - 985 Counties						
Number of Years of Average Previous Net Value	**1 Year**		**3 Year**		**5 Year**	
Net Value	0.0011		0.0039		0.0096	*
	(0.0014)		(0.0029)		(0.0043)	
Expected Revenue - Corn	0.0156	***	0.0157	***	0.0158	***
	(0.0019)		(0.0019)		(0.0019)	
Expected Revenue - Soybeans	0.0034		0.0033		0.0031	
	(0.0027)		(0.0027)		(0.0027)	
Spatial Error Coefficient	-0.624	***	-0.624	***	-0.624	***
	0.0239		0.0239		0.0239	
Spatial Lag Coefficient	0.911	***	0.911	***	0.911	***
	0.0057		0.0057		0.0057	
r^2	0.98175		0.98175		0.98176	
Observations	7880		7880		7880	
Counties	985		985		985	
*P<0.05, **p<0.01, ***p<0.001; Standard errors in parentheses						

Table 11:

Marginal Effects Midwest - 985 Counties									
Number of Years of Average Previous Net Value	1 Year			3 Year			5 Year		
	Direct	Indirect	Total	Direct	Indirect	Total	Direct	Indirect	Total
Net Value	0.002	0.009	0.011	0.008	0.034	0.041	0.019 *	0.083 *	0.102 *
	(0.449)	(0.449)	(0.449)	(0.212)	(0.212)	(0.212)	(0.040)	(0.041)	(0.040)
Expected Revenue - Corn	0.030 ***	0.135 ***	0.165 ***	0.031 ***	0.136 ***	0.166 ***	0.031 ***	0.136 ***	0.166 ***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Expected Revenue - Soybeans	0.007	0.029	0.036	0.006	0.028	0.035	0.006	0.027	0.033
	(0.282)	(0.285)	(0.285)	(0.267)	(0.269)	(0.268)	(0.267)	(0.269)	(0.269)

*P<0.05, **p<0.01, ***p<0.001; Standard errors in parentheses

Table 12:

SARAR Regressions on Fixed Effect Estimates Midwest - 985 Counties						
Number of Years of Average Previous Net Value	**1 Year**		**3 Year**		**5 Year**	
Soil	51.57	***	51.66	***	51.57	***
	(4.2616)		(4.2603)		(4.2616)	
StDev - Corn	0.0976		0.0953		0.0976	
	(0.0771)		(0.0771)		(0.0771)	
StDev - Soybeans	-0.6222	**	-0.6210	**	-0.6222	**
	(0.2257)		(0.2258)		(0.2257)	
GDD	-0.0025	**	-0.0025	**	-0.0025	**
	(0.0009)		(0.0009)		(0.0009)	
Spatial Error Coefficient	-0.5050	***	-0.5066	***	-0.5090	***
	(0.1080)		(0.1078)		(0.1071)	
Spatial Lag Coefficient	0.4372	***	0.4388	***	0.4420	***
	(0.0838)		(0.0835)		(0.0828)	
AIC	7611.5		7611.8		7612.7	
Observations	985		985		985	
Counties	985		985		985	
*P<0.05, **p<0.01, ***p<0.001; Standard errors in parentheses						

Table 13:

SARAR Random Effects Panel Model Midwest - 985 Counties						
Number of Years of Average Previous Net Value	**1 Year**		**3 Year**		**5 Year**	
Net Value	0.0016		0.0008		0.0101	*
	0.0017		0.0076		0.0050	
Soil	42.40	***	94.25	***	42.74	***
	2.5480		7.4270		2.5539	
Expected Revenue - Corn	0.0208	***	0.0476	***	0.0209	***
	0.0020		0.0047		0.0020	
Expected Revenue - Soybeans	0.0056	*	0.0123	**	0.0055	*
	0.0028		0.0037		0.0027	
GDD	-0.0021	**	0.0068		-0.0021	**
	0.0008		0.0029		0.0008	
Corn StDev	0.174	**	-0.011		0.164	**
	0.0618		0.0939		0.0621	
Soybeans StDev	-0.61	**	-0.35	*	-0.60	**
	0.1912		0.2741		0.1912	
Time Fixed Effects	YES		YES		YES	
State Fixed Effects	YES		YES		YES	
Spatial Error Coefficient	-0.474	***	-0.564	***	-0.470	***
	0.0273		0.0248		0.0272	
Spatial Lag Coefficient	0.879	***	0.947	***	0.879	***
	0.0070		0.0043		0.0069	
r^2	0.81549		0.80573		0.81581	
Observations	7880		7880		7880	
Counties	985		985		985	

Table 14:

Panel Fixed Effects Model - Non-Spatial Midwest - 985 Counties						
Number of Years of Average Previous Net Value	**1 Year**		**3 Year**		**5 Year**	
Net Value	0.0019		0.1155	***	0.3325	***
	0.0050		0.0099		0.0127	
Expected Revenue - Corn	-0.0089	***	-0.0016		-0.0009	
	0.0022		0.0022		0.0021	
Expected Revenue - Soybeans	0.1324	***	0.1105	***	0.1065	***
	0.0044		0.0047		0.0043	
Spatial Error Coefficient	No		No		No	
Spatial Lag Coefficient	No		No		No	
r^2	0.28542		0.29917		0.35003	
Observations	7880		7880		7880	
Counties	985		985		985	
*P<0.05, **p<0.01, ***p<0.001; Standard errors in parentheses						

Table 15:

SARAR Fixed Effects Panel Model Northern Plains - 288 Counties						
Number of Years of Average Previous Net Value	**1 Year**		**3 Year**		**5 Year**	
Net Value	0.0002		0.0065		0.0298	**
	(0.0030)		(0.0063)		(0.0095)	
Expected Revenue - Corn	0.0092	**	0.0092	***	0.0095	***
	(0.0028)		(0.0028)		(0.0028)	
Expected Revenue - Soybeans	0.0035		0.0032		0.0024	
	(0.0042)		(0.0042)		(0.0042)	
Spatial Error Coefficient	-0.366	***	-0.366	***	-0.363	***
	0.0542		0.0542		0.0544	
Spatial Lag Coefficient	0.917	***	0.917	***	0.914	***
	0.0111		0.0111		0.0115	
r^2	0.98153		0.98153		0.98155	
Observations	2304		2304		2304	
Counties	288		288		288	
*P<0.05, **p<0.01, ***p<0.001; Standard errors in parentheses						

Table 16:

SARAR Fixed Effects Panel Model Lake States - 223 Counties						
Number of Years of Average Previous Net Value	**1 Year**		**3 Year**		**5 Year**	
Net Value	-0.0012		0.0256	**	0.0268	*
	(0.0068)		(0.0093)		(0.0125)	
Expected Revenue - Corn	0.1122	***	0.0496	***	0.0488	***
	(0.0133)		(0.0068)		(0.0067)	
Expected Revenue - Soybeans	0.0059		-0.0040		-0.0041	
	(0.0061)		(0.0047)		(0.0047)	
Spatial Error Coefficient	-0.224	**	-0.219	**	0.227	**
	0.0712		0.0743		0.0738	
Spatial Lag Coefficient	0.838	***	0.817	***	0.820	***
	0.0235		0.0256		0.0251	
r^2	0.91793		0.97485		0.97483	
Observations	1784		1784		1784	
Counties	223		223		223	
*P<0.05, **p<0.01, ***p<0.001; Standard errors in parentheses						

Table 17:

SARAR Fixed Effects Panel Model Corn Belt - 474 Counties						
Number of Years of Average Previous Net Value	**1 Year**		**3 Year**		**5 Year**	
Net Value	0.0037		0.0046		0.0012	
	(0.0024)		(0.0047)		(0.0069)	
Expected Revenue - Corn	0.0202	***	0.0193	***	0.0192	***
	(0.0047)		(0.0047)		(0.0047)	
Expected Revenue - Soybeans	0.0348	***	0.0363	***	0.0352	***
	(0.0089)		(0.0090)		(0.0089)	
Spatial Error Coefficient	-0.627	***	-0.627	***	-0.627	***
	0.0306		0.0306		0.0306	
Spatial Lag Coefficient	0.875	***	0.875	***	0.875	***
	0.0100		0.0100		0.0099	
r^2	0.97366		0.97366		0.97366	
Observations	3792		3792		3792	
Counties	474		474		474	
*P<0.05, **p<0.01, ***p<0.001; Standard errors in parentheses						

Table 18:

SARAR Fixed Effects Panel Model Iowa - 99 Counties						
Number of Years of Average Previous Net Value	**1 Year**		**3 Year**		**5 Year**	
Net Value	0.0233	*	0.0214		0.0048	
	0.0094		0.0186		0.0285	
Expected Revenue - Corn	0.0866	***	0.0807	***	0.0749	***
	0.0226		0.0226		0.0225	
Expected Revenue - Soybeans	0.0205		0.0320		0.0302	
	0.0514		0.0513		0.0515	
Spatial Error Coefficient	-0.402	**	-0.407	**	-0.399	**
	0.1359		0.1346		0.1351	
Spatial Lag Coefficient	0.803	***	0.812	***	0.813	***
	0.0441		0.0424		0.0426	
r^2	0.98153		0.98153		0.98155	
Observations	792		792		792	
Counties	99		99		99	
*P<0.05, **p<0.01, ***p<0.001; Standard errors in parentheses						

CHAPTER 6 – CONCLUSION

Crop insurance has changed drastically over the past 70 years. RMA and other agencies continue to improve the performance of products offered to producers, driven largely by the increased quantity and quality of data. Demand from the public and the agricultural industry for better performance from crop insurance products will continue to drive innovation in the Federal crop insurance program. However, the rating system is a slowly healing mechanism that has developed spatially correlated patterns of over-payments and under-payments. While crop insurance should pay out the subsidy per acre on average, net value from crop insurance is often a significantly different value, even when averaged through time and space. For now, the variation in net value from crop insurance across counties, states, and regions provide excellent opportunities for analysis. This study confirms that producers factor a proportion of crop insurance into cash rents as the consistency of net value of crop insurance increases. However, the magnitude to which producers factor a proportion of net value into cash rents contrasts previous analyses of different forms of government payments.

Given the complexity of the data and the way in which the data were aggregated, the true impact of the net value of crop insurance on cash rents is difficult to disentangle. Thus, one must avoid the fallacy of the inverse when interpreting the results in this analysis. Simply because the economic significance of the results is difficult to directly assess, it does not imply the elimination of the Federal crop insurance program would not have significant economic consequences. The determination of crop insurance premiums, how cash rents are established, and whether a producer elects to purchase crop insurance are so intertwined that the modeling approach used in this analysis likely diminishes the results.

The inclusion of much more granular data would immensely aid a future study of this nature. Nuances, such as preventive plant or specific products, may exist in the crop insurance program that producers exploit more or less frequently than other aspects of the program. While not currently feasible, the reconciliation of data on farmland values and attributes, producer characteristics, and parcel-specific crop insurance loss history would paint a more vivid picture of the impact of crop insurance on cash rents. Big data will undoubtedly serve a larger role in the success or failure of the Federal crop insurance program moving forward.

The findings in this thesis provide valuable insight to policy planners in the future Farm Bill debates. The balance between large enough subsidy rates to maintain widespread participation while simultaneously facing scrutiny over the scale of the federal crop insurance program will continue to challenge lawmakers. As margins for producers tighten due to depressed commodity prices, producers may either embrace crop insurance as a valuable risk management tool or opt to forgo the purchase of crop insurance altogether. While subsidies have helped lower the cost of crop insurance for producers, producers operating on low risk farmland are the most likely candidates to first opt out of crop insurance. This move would only exacerbate the problems of adverse selection and moral hazard that historically plagued crop insurance.

Government support for agriculture remains an important factor in the evolution of the agricultural industry. Economies of scale and scope continue to drive consolidation while simultaneously promoting efficiencies. Technology and precision agriculture aid in the migration towards increasingly efficient operations, but at an ever-increasing cost to producers. Federal farm programs enhance a producer’s ability to address inefficiencies through capital investments. While moral hazard historically has plagued the crop insurance program, the program also encourages capital investments that improve efficiencies. As cash rent leasing agreements continue to grow in popularity, crop insurance's role as a revenue safety net will also continue to grow.

The identification strategy used in this analysis performs best with RMA data. However, tools such as *iFarm*'s crop insurance decision tool may prove more useful in predicting future year's net values. The *iFarm* net cost values represent the expected long run averages plus/minus some effect of the most recent events, and are more responsive to rating changes. Further study of the effect of the net value of crop insurance is needed as producers learn from their own experiences with crop insurance.

The research question and subsequent results outlined in this analysis represent a small fraction of the research that focuses on the impacts government payments can have farmland values. As government payments to producers change and are refined, how producers respond to these programs will undoubtedly present future researchers with both identification challenges and analysis opportunities. The ability to quantify the impacts of any form of government payments to producers is valued by producers, lenders, investors, and anyone else with a stake in agriculture.

REFERENCES

Allen, D., & Lueck, D. (1992). Contract Choice in Modern Agriculture: Cash Rent versus Cropshare. *The Journal of Law & Economics, Vol. 35, No. 2* , 397-426.

Alston, J. M. (1986). An Analysis of Growth of U.S. Farmland Prices, 1963-82. *American Journal of Agricultural Economics, Vol. 68, No. 1*, 1-9.

Anselin, L. (1992). Space and Applied Econometrics. *Regional Science and Urban Economics 22(3)*, 307-316.

Anselin, L. (2002). Issues in the Specification and Interpretation of Spatial Regression Models. *Agricultural Economics 27*, 247-267.

Anselin, L., & Bera, A. (1998). “Spatial dependence in linear regression models with an introduction to spatial econometrics. In D. Giles, *Handbook of Applied Economic Statistics* (pp. 237-289). New York: Marcel Dekker.

Anselin, L., Le Gallo, J., & Jayet, H. (2008). Spatial Panel Econometrics. In *The Econometrics of Panel Data* (pp. 625-660). Springer Berlin Heidelberg.

Baltagi, B. H., Song, S. H., & Koh, W. (2003). Testing Panel Data Regression MOdels with Spatial Error Correlation. *Journal of Econometrics*, 123-150.

Barnard, C. H., Nehring, R., Ryan, J., & Collender, R. (2001). HIgher Cropland Value from Farm Program Payments: Who Gains? *USDA Economic Research Service Agricultural Outlook*, 26-30.

Barnard, C. H., Whittaker, G., Westenbarger, D., & Ahearn, M. (1997). Evidence of Capitalization of Direct Government Payments into U.S. Cropland Values. *American Journal of Agricultural Economics, Vol. 79, No. 5*, 1642-1650.

Barry, P. J., Moss, L. M., Sotomayor, N. L., & Escalante, C. L. (2000). Lease Pricing for Farm Real Estate. *Review of Agricultural Economics, Vol. 22, No. 1*, 2-16.

Bastian, C. T., Germino, M. J., Reiners, W. A., & Blasko, B. J. (2002). Environmental Amenities and Agricultural Land Values: A Hedonic Model Using Geographic Information Systems Data. *Ecological Economics 40, no. 3*, 337-349.

Baylis, K., Paulson, N. D., & Piras, G. (2011). Spatial Approaches to Panel Data in Agricultural Economics: A Climate Change Application. *Journal of Agricultural and Applied Economics, 43, 3*, 325-338.

Benirschka, M., & Binkley, J. K. (1994). Land Price Volatility in a Geographically Dispersed Market. *American Journal of Agricultural Economics, Vol. 76, No. 2*, 185-195.

Can, A., & Megbolugbe, I. (1997). Spatial Dependence and House Price Index Construction. *The Journal of Real Estate Finance and Economics, vol. 14, issue 1-2*, 203-222.

Carson, N., & Langemeier, M. (2017). Relationship between Cash Rent and Net Return to Land. *farmdoc daily (7):69*.

Chicoine, D. L. (1981). Farmland Values at the Urban Fringe: An Analysis of Sale Prices. *Land Economics 57, no. 3*, 353-362.

Drescher, K., Henderson, J., & McNamara, K. (2001). Farmland Price Determinants. *American Agricultural Economics Association Annual Meeting.* Chicago, Illinois.

Du, X., Hennessy, D., & Edwards, W. (2007). *Determinants of Iowa Cropland Cash Rental Rates: Testing Ricardian Rent Theory.* Ames, IA: Iowa State University.

Du, X., Hennessy, D., & Edwards, W. (2008). Does a Rising Biofuels Tide Raise All Boats? A Study of Cash Rent Determinants for Iowa Farmland under Hay and Pasture. *Journal of Agriculture and Food Industrial Organization 6(2)*.

Elhorst, J. (244-268). Specification and Estimation of Spatial Panel Data Models. *International Regional Science Review 26(3)*, 2003.

Elhorst, J. P. (2011). *Spatial panel models.*

Falk, B. (1991). Formally Testing the Present Value Model of Farmland Prices. *American Journal of Agricultural Economics, Vol. 73, No. 1*, 1-10.

FBM. (2016). *Control of Illinois Farmland, FBM-324.* Urbana-Champaign: University of Illinois. Retrieved from Farm Business Management.

Featherstone, A. M., & Baker, T. G. (1988). Effects of Reduced Price and Income Supports on Farmland Rent and Value. *North Central Journal of Agricultural Economics, Vol. 10, No. 2*, 177-189.

Floyd, J. E. (1965). The Effects of Farm Price Supports on the Returns to Land and Labor in Agriculture. *Journal of Political Economy, Vol. 73, No. 2*, 148-158.

Goodwin, B. K., & Ortalo-Magne, F. (1992). The Capitalization of Wheat Subsidies into Agricultural Land Values. *Canadian Journal of Agricultural Economics*, 37-54.

Goodwin, B. K., & Smith, V. H. (1995). *The Economics of Crop Insurance and Disaster Aid.* Washington, D.C.: The AEI Press.

Goodwin, B. K., Vandeveer, M. L., & Deal, J. L. (2004). An Empirical Analysis Of Acreage Effects Of Participation In The Federal Crop Insurance Program. *American Journal of Agricultural Economics 86(4)*, 1058-1077.

Griffith, D. (1987). Spatial Autocorrelation: A Primer. *American Association of Geographers.* Washington, D.C.

Guiling, P., Brorsen, B. W., & Doye, D. G. (2007). How Much Influence Does Recreation Have on Agricultural Values. *Southern Economics Association Annual Meeting.* Mobile, AL.

Hanson, E. D. (2012). *Determinates of Illinois Farmland Prices.* Urbana-Champaign: University of Illinois - Masters Thesis.

Hausman, J. (1978). Specification Tests in Econometrics. *Econometrica, Vol. 46, Issue 6*, 1251-1271.

Helmers, G. A. (2004). *Land Valuation and the Income Capitalization Model, Paper 177.* Lincoln: Cornhusker Economics - University of Nebraska.

Henderson, J. R., & Moore, S. (2003). The Capitalization of Wildlife Recreation Income into Farmland Values. *Journal of Agricultural and Applied Economics 38, no. 3* , 597-610.

Hennessy, D. A. (1998). The Production Effects of Agricultural Income Support Policies under Uncertainty. *American Journal of Agricultural Economics*, 46-57.

Herdt, R. W., & Cochrane, W. W. (1966). Farm Land Prices and Farm Technological Advance. *Journal of Farm Economics, Vol. 48, No. 2*, 243-263.

Hollinger, S., & Angel, J. R. (2009). Weather and Crops. In *Illinois Agronomy Handbook.* Urbana-Champaign: University of Illinois.

Hölmstrom, B. (1979). Moral Hazard and Observability. *The Bell Journal of Economics, Vol. 10, No. 1* , 74-91.

Huang, H., Miller, G. Y., Sherrick, B. J., & Gomez, M. I. (2006). Factors Influencing Illinois Farmland Values. *American Journal of Agricultural Economics, Vol. 88, No. 2*, 458-470.

Ifft, J., Wu, S., & Kuethe, T. (2014). The Impact of Pasture Insurance on Farmland Values. *Agricultural and Resource Economics Review 43/3*, 390-405.

Kirwan, B. (2014). The Crowd-out Effect of Crop Insurance on Farm Survival and Profitability. *Agricultural & Applied Economics Association.* Minneapolis.

Lancaster, K. J. (1966). A New Approach to Consumer Theory. *Journal of Political Economy, Vol. 74, No. 2*, 132-157.

Langemeier, M. R. (2013). Impact of Crop Insurance Indemnity Payments on Cash Rent and Land Values. *AAEA Crop Insurance and Farm Bill Symposium.* Louisville.

Lee, L.-f., & Yu, J. (2008). *Estimation of Spatial Autoregressive Panel Data Models with Fixed Effects (Working Paper).* Syracuse, New York: Syracuse University.

LeSage, J. P., & Pace, R. K. (2004). Models for Spatially Dependent Missing Data. *The Journal of Real Estate Finance and Economics*, 233-254.

Livanis, G., Moss, C. B., Breneman, V. E., & Nehring, R. F. (2006). Urban Sprawl and Farmland Prices. *American Journal of Agricultural Economics 88* , 915-929.

Makki, S. S., & Somwaru, A. (2001). Evidence of Adverse Selection in Crop Insurance Markets. *The Journal of Risk and Insurance, Vol. 68, No. 4* , 685-708.

Melichar, E. (1979). Capital Gains versus Current Income in the Farming Sector. *American Journal of Agricultural Economics, Vol. 61, No. 5*, 1085-1092.

Millo, G., & Piras, G. (2012). splm: Spatial Panel Data Models in R. *Journal of Statistical Software*.

Miranda, M. (1991). Area-yield crop insurance reconsidered. *American Journal of Agricultural Economics, 73*, 233-242.

Moran, P. A. (1950). Notes on Continuous Stochastic Phenomena. *Biometrika 37, no. 1*, 17-23.

Nickerson, C., Morehart, M., Kuethe, T., Beckman, J., Ifft, J., & Williams, R. (2012). *Trends in U.S. Farmland Values and Ownership.* Economic Research Service.

Osland, L. (2013). The importance of unobserved attributes in hedonic house price models. *International Journal of Housing Markets and Analysis, Vol. 6 Issue: 1*, 63-78.

Pace, R. K. (2009). *Introduction to Spatial Econometrics.* Boca Raton, FL: Chapman &Hall/CRC.

Pace, R. K., & LeSage, J. P. (2008). A spatial Hausman test. *Economic Letters, Volume 101, Issue 3*, 282-284.

Palmquist, R. B., & Danielson, L. E. (1989). A Hedonic Study of the Effects of Erosion Control and Drainage on Farmland Values. *American Journal of Agricultural Economics, Vol. 71, No. 1* , 55-62.

Patton, M., & McErlean, S. (2003). Spatial Effects within the Agricultural Land Market in Northern Ireland. *Journal of Agricultural Economics*, 35-54.

Phipps, T. T. (1984). Land Prices and Farm-Based Returns. *American Journal of Agricultural Economics, Vol. 66, No. 4*, 422-429.

Plantinga, A. J., Lubowski, R. N., & Stavins, R. N. (2002). The Effects of Potential Land Development on Agricultural Land Prices. *Journal of Urban Economics 52, no. 3*, 561-581.

Pope, R. D., Kramer, R. A., Green, R. D., & Gardner, B. D. (1979). An Evaluation of Econometric Models of U.S. Farmland Prices. *Western Journal of Agricultural Economics, Vol. 4, No. 1* , 107-119.

Ricardo, D. (1817). *On the Principles of Political Economy and Taxation.* London.

Ricardo, D. (1821). *On the Principles of Political Economy and Taxation.* London: John Murray.

RMA. (2017, May 7). *Summary of Business Reports and Data*. Retrieved from USDA Risk Management Agency: https://www.rma.usda.gov/data/sob.html

Schnitkey, G. (2016). Rising Interest Rates and Farmland Prices. *farmdoc daily (6):236*.

Schnitkey, G. D., & Sherrick, B. J. (2011). *Income and Capitalization Rate Risk in Agricultural Real Estate Markets.* Agricultural & Applied Economics Association.

Sherrick, B. J., Barry, P. J., Schnitkey, G. D., Ellinger, P. N., & Wansink, B. (2003). Farmers' Preferences for Crop Insurance Attributes. *Review of Agricultural Economics, Vol. 25, No. 2* , 415-429.

Shiller, R. J. (1984). *Stock Prices and Social Dynamics.* Brookings Papers on Economic Activity.

Shoemaker, R. (1989). Agricultural Land Values and Rents under the Conservation Reserve Program. *Land Economics*, 131-137.

Shoemaker, R., Anderson, M., & Hrubovcak, J. (1990). US Farm Programs and Agricultural Resources. *Agriculture Information Bulletin - United States Department of Agriculture No.614 pp.12*.

Smith, V. H., & Goodwin, B. K. (1996). Crop Insurance, Moral Hazard, and Agricultural Chemical Use. *American Journal of Agricultural Economics, Vol. 78, No. 2*, 428-438.

Soto, P. (2004). *Spatial Econometric Analysis on Louisiana Rural Real Estate Values.* Baton Rouge, Lousiana: Lousiana State University.

Stewart, P. A., & Libby, L. W. (1998). Determinants of Farmland Value: The Case of DeKalb County, Illinois. *Review of Agricultural Economics 20, no. 1* , 80-95.

Tobler, W. (1979). Lattice Tuning. *Geographical Analysis*, 36-44.

Tweeten, L. G., & Martin, J. E. (1966). A Methodology for Predicting U.S. Farm Real Estate Price Variation. *Journal of Farm Economics, Vol. 48, No. 2* , 378-393.

USDA. (2017, May 7). *Quick Stats*. Retrieved from National Agricultural Satatistics Service: https://quickstats.nass.usda.gov/

Van Herck, K., Swinnen, J., & Vranken, L. (2013). *Direct Payments and Land Rents Evidence from New Member States (Working Paper).* Brussels, Belgium: Factor Markets.

Vedenov, D. V., & Barnett, B. J. (2004). Efficiency of Weather Derivatives as Primary Crop Insurance Instruments. *Journal of Agricultural and Resource Economics, Vol. 29, No. 3*, 387-403.

Veeman, M., Dong, X.-y., & Veeman, T. S. (1993). Price Behavior of Canadian Farmland. *Canadian Journal of Agricultural Economics*, 197-208.

Viton, P. (2010). Notes on Spatial Econometric Models. *City and Regional Planning, 870 (3)*, 2-17.

Ward, B. (2016). *WESTERN OHIO CROPLAND VALUES AND CASH RENTS 2015-16.* Columbus: Ohio State University.

Weersink, A., Clark, S., Turvey, C. G., & Sarker, R. (1999). The Effect of Agricultural Policy on Farmland Values. *Land Economics, Vol. 75, No. 3*, 425-439.

Williams, J., Renard, K., & Dyke, P. (1983). EPIC: a new method for assessing erosion's effect on soil productivity. *Journal of Soil and Water Conservation*, 381-383.

Woodard, S. M. (2010). *A Spatial Analysis of Illinois Agricultural Cash Rents.* University of Illinois.

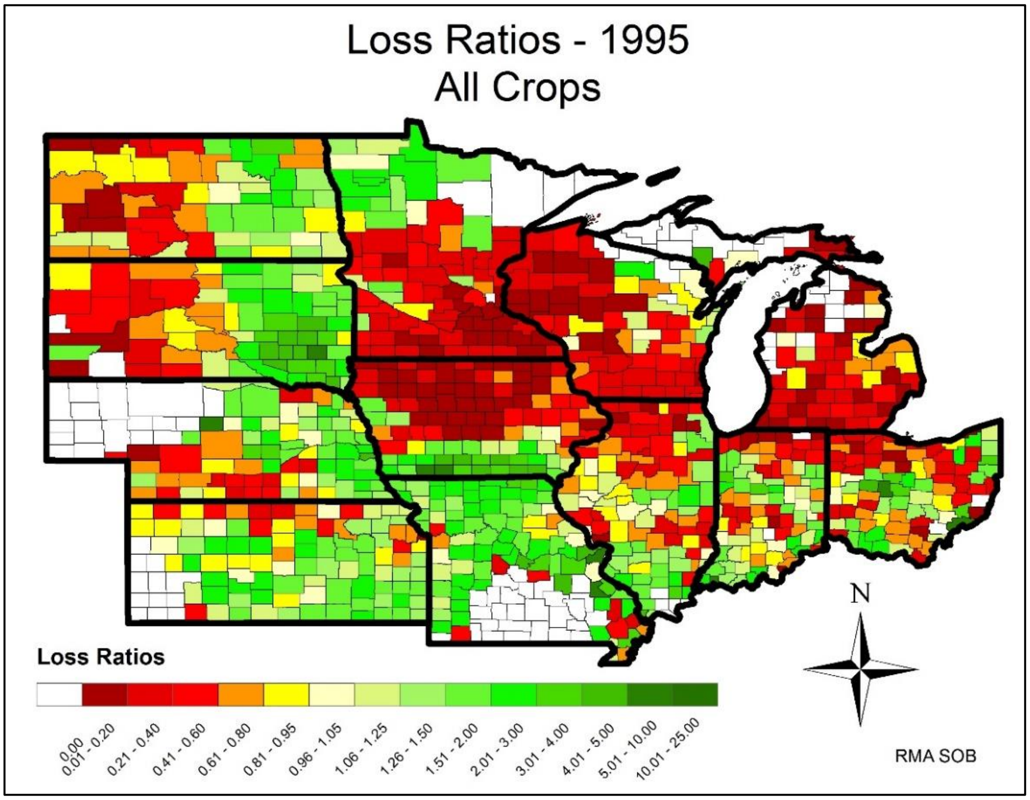
Yang, S., Logan, J., & Coffey, D. L. (1995). Mathematical formulae for calculating the base temperature for growing degree days. *Agricultural and Forest Meteorology, Vol. 74, Issues 1-2*, 61-74.

Zulauf, C. (2016, April 20). *Why Crop Insurance Has Become an Issue*. Retrieved from farmdoc daily (6):76: http://farmdocdaily.illinois.edu/2016/04/why-crop-insurance-has-become-an-issue.html

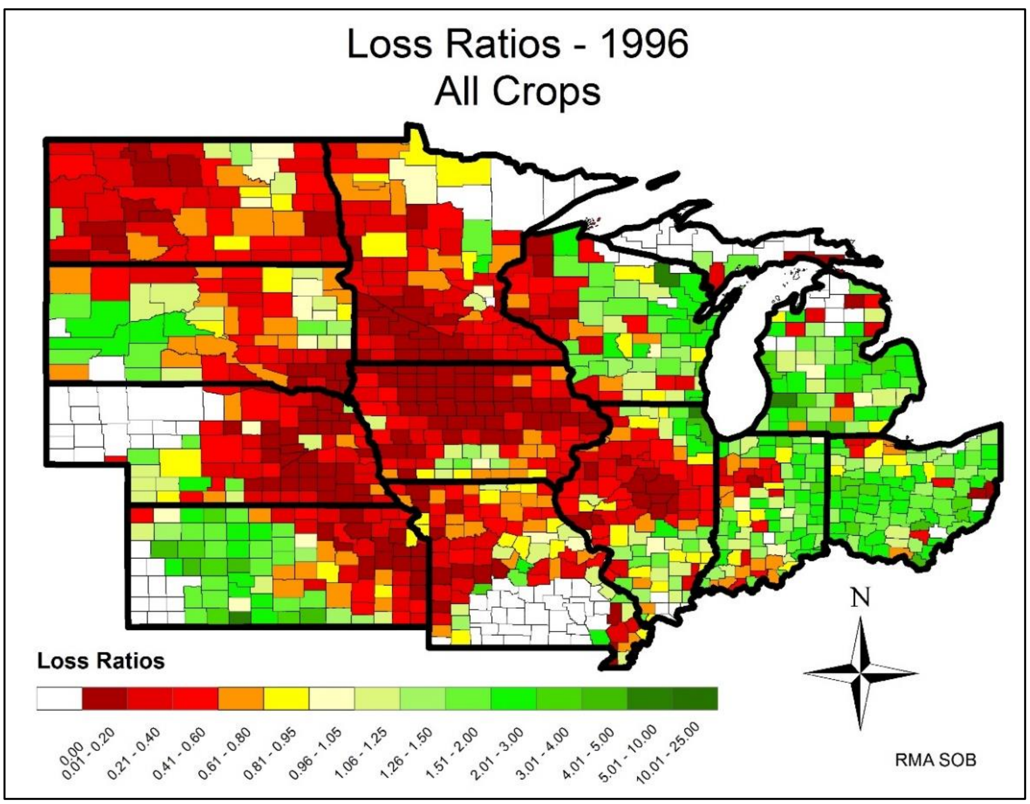
Zulauf, C., Demircan, V., Schnitkey, G., Barnaby, A., & Herbel, K. (2013). Examining Contemporaneous Farm and County Losses Using Farm Level Data. *AAEA Crop Insurance and Farm Bill Symposium.* Louisville, KY: AAEA.

APPENDIX A: CROP INSURANCE LOSS RATIO MAPS

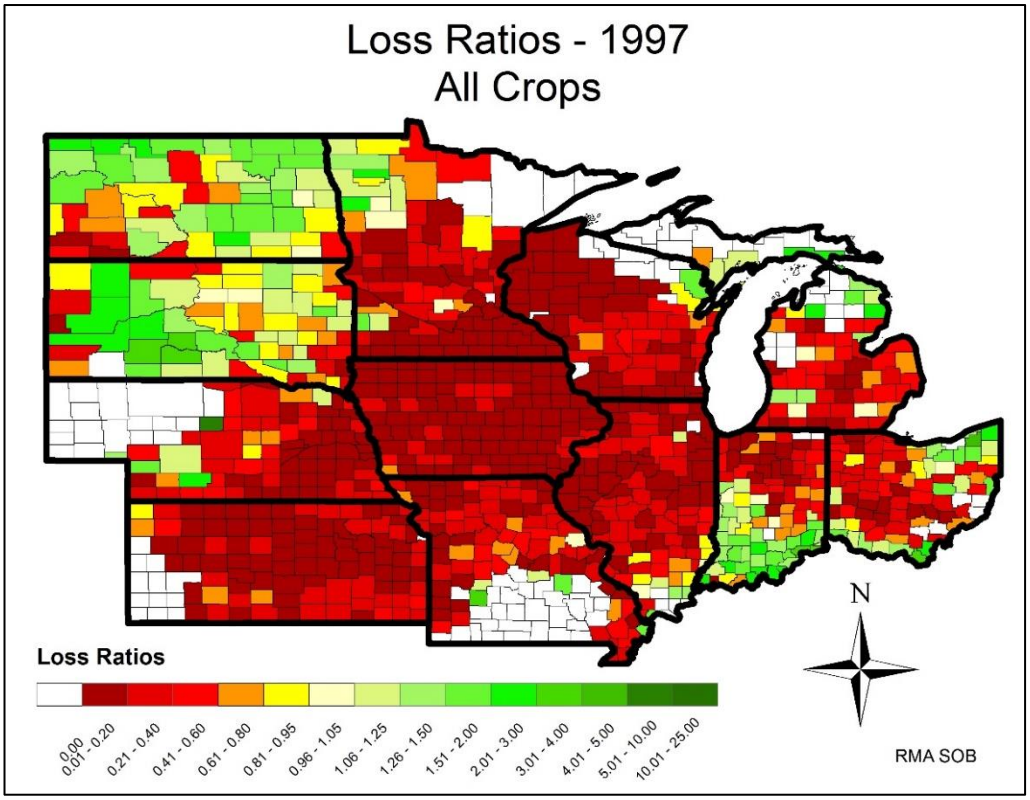
A1:



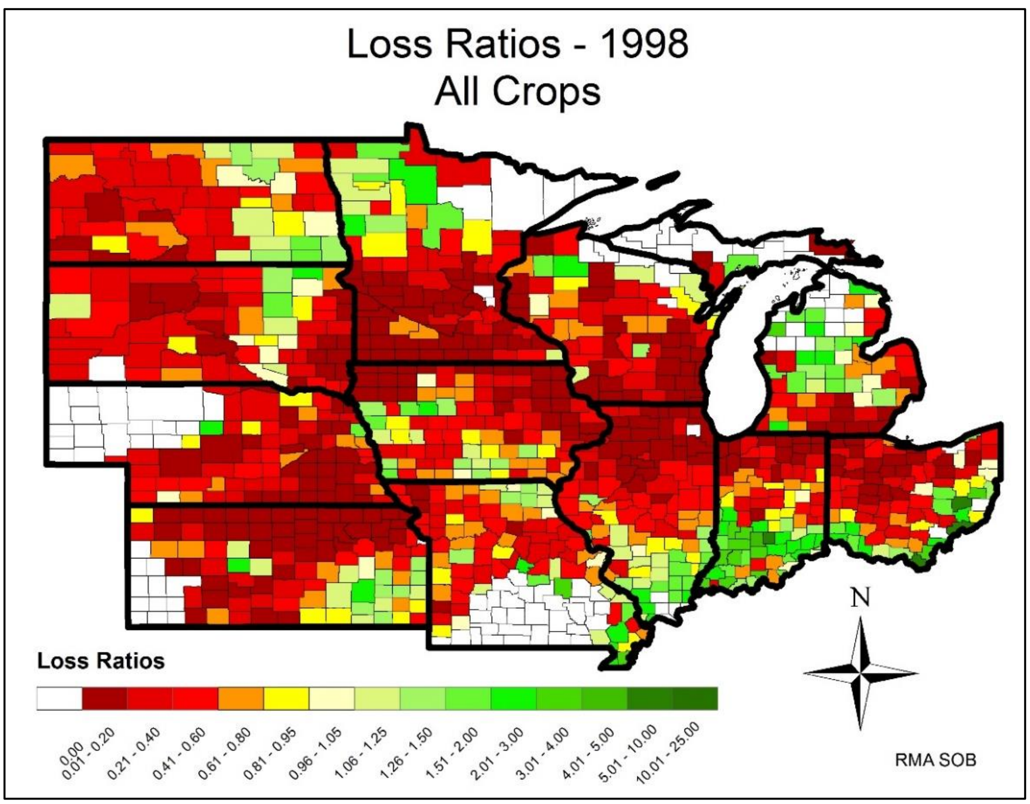
A2:



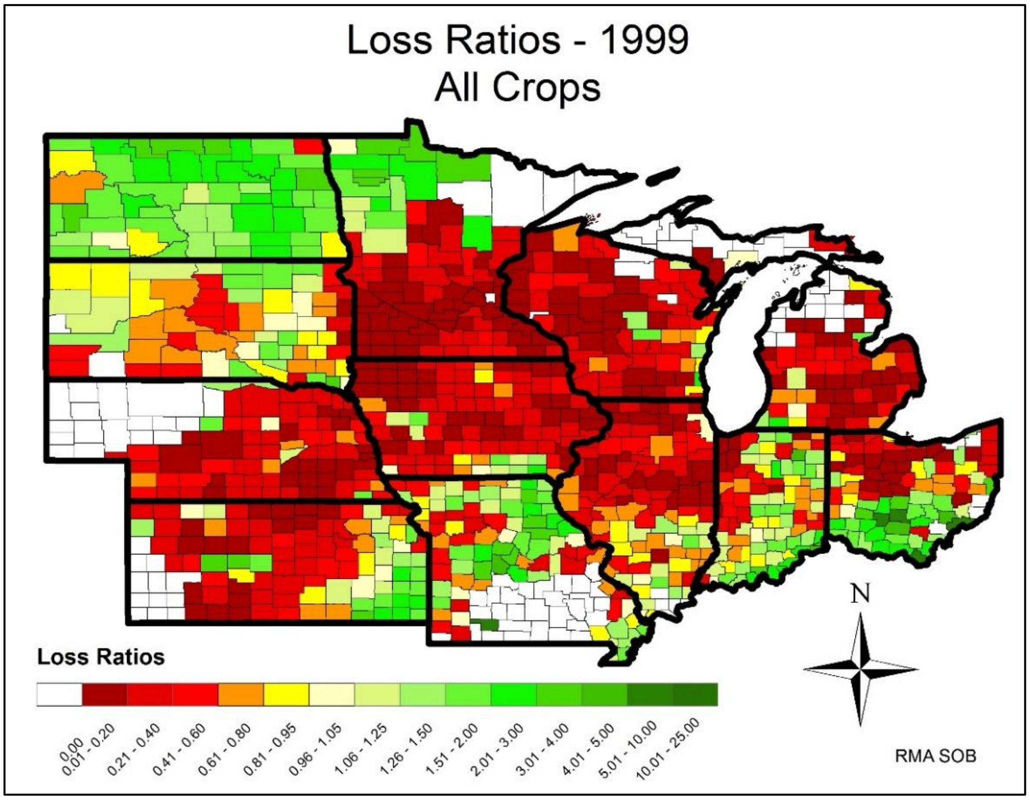
A3:


Loss Ratios - 1997
All Crops
N
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
RMA SOB

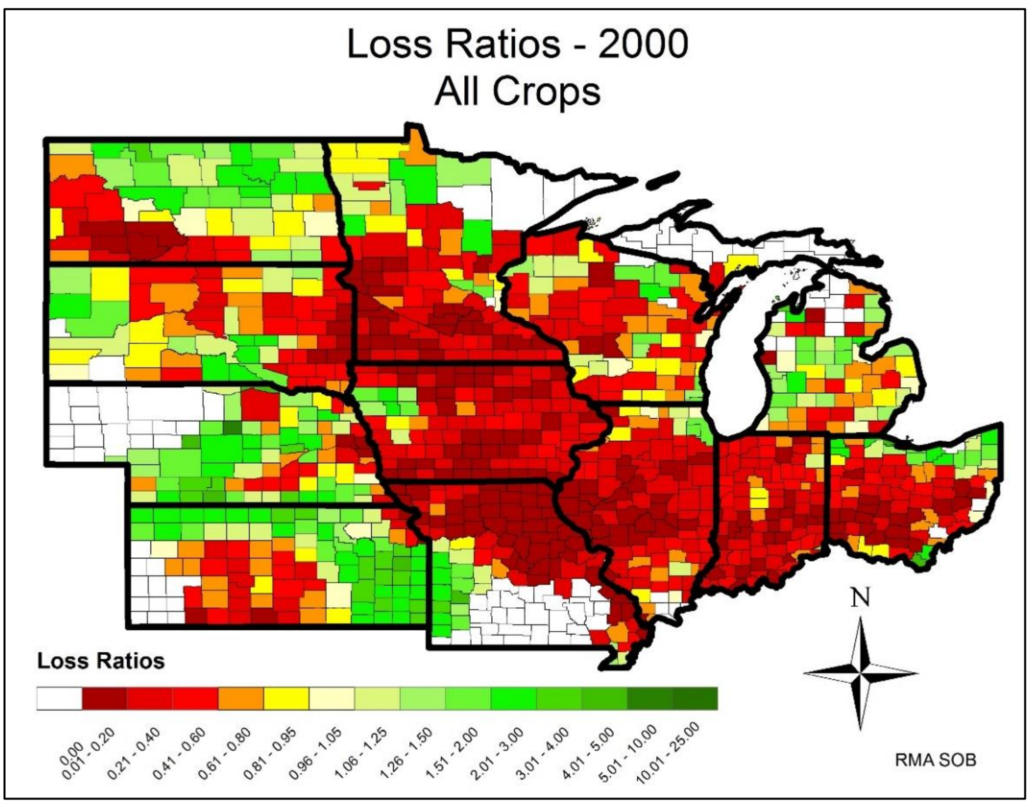
A4:


Loss Ratios - 1998
All Crops
N
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
RMA SOB

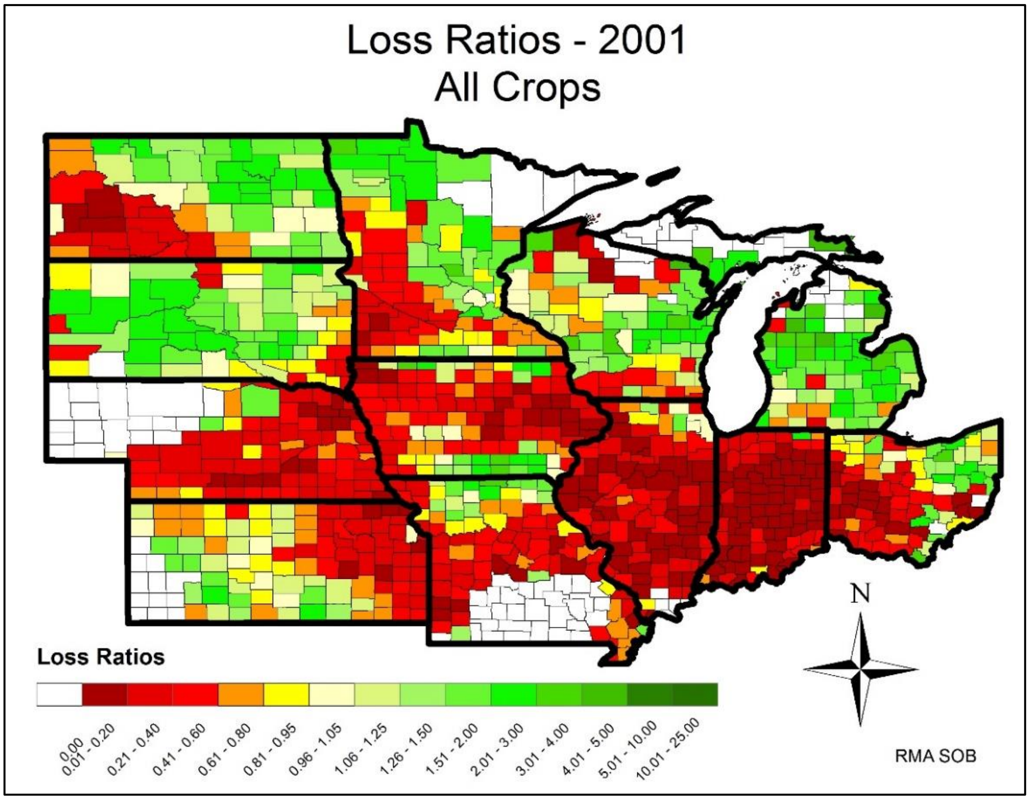
A5:


Loss Ratios - 1999
All Crops
N
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
RMA SOB

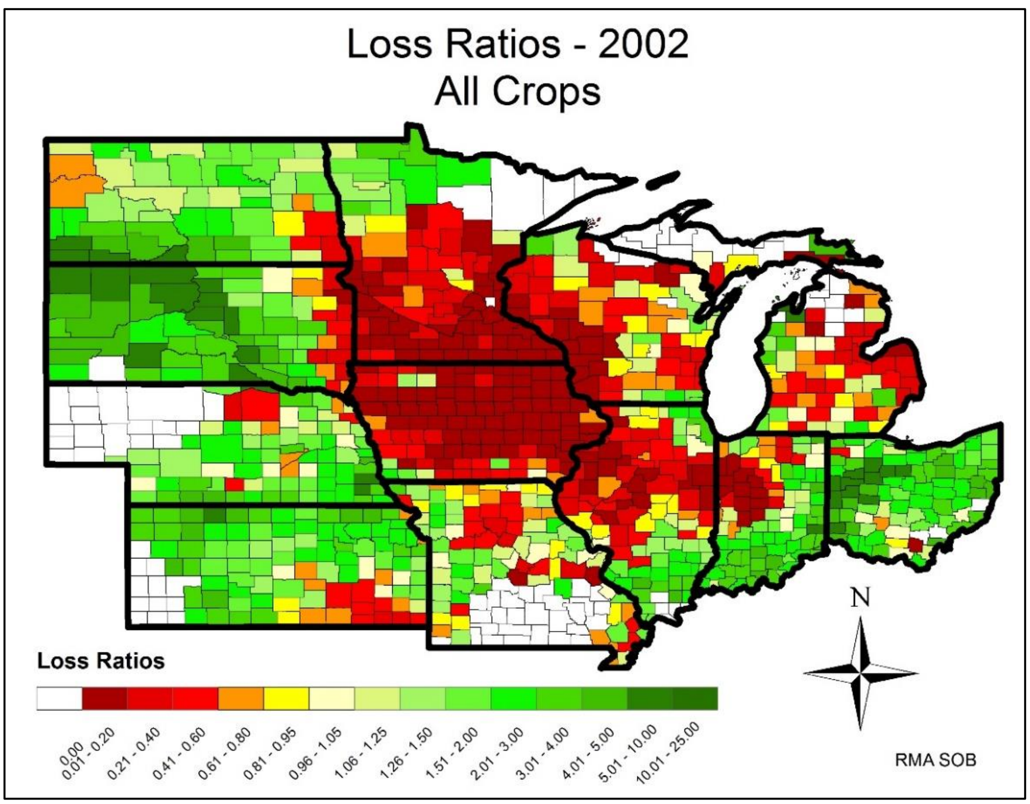
A6:


Loss Ratios - 2000
All Crops
N
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
RMA SOB

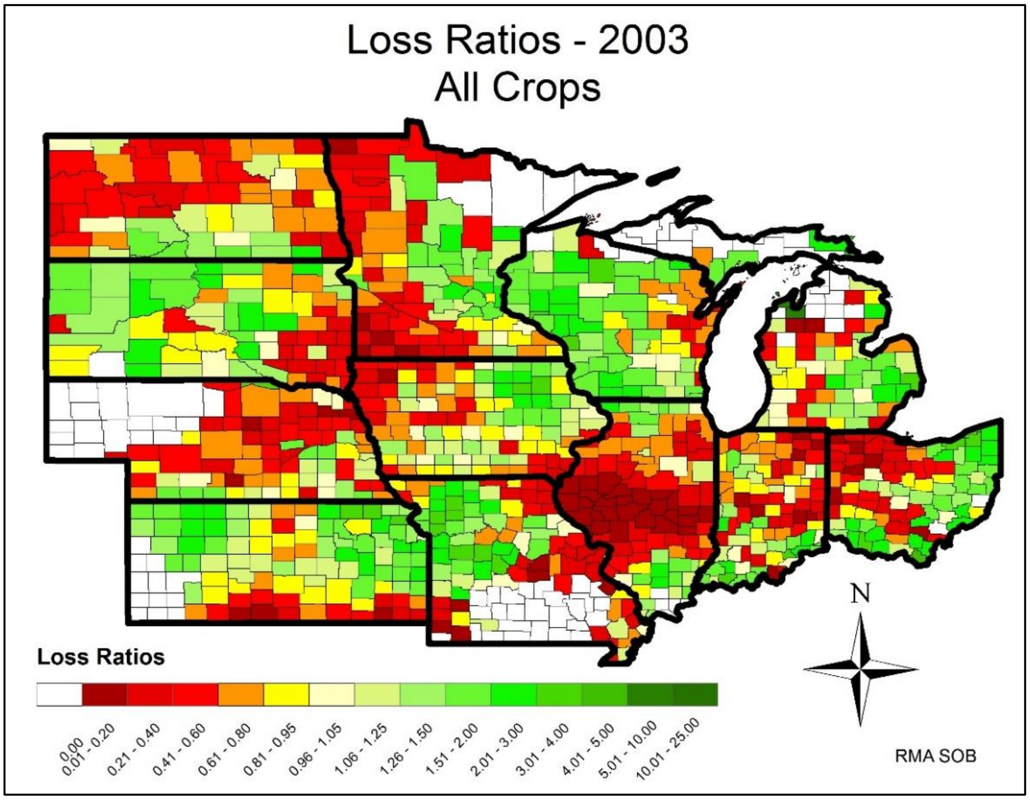
A7:


Loss Ratios - 2001
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

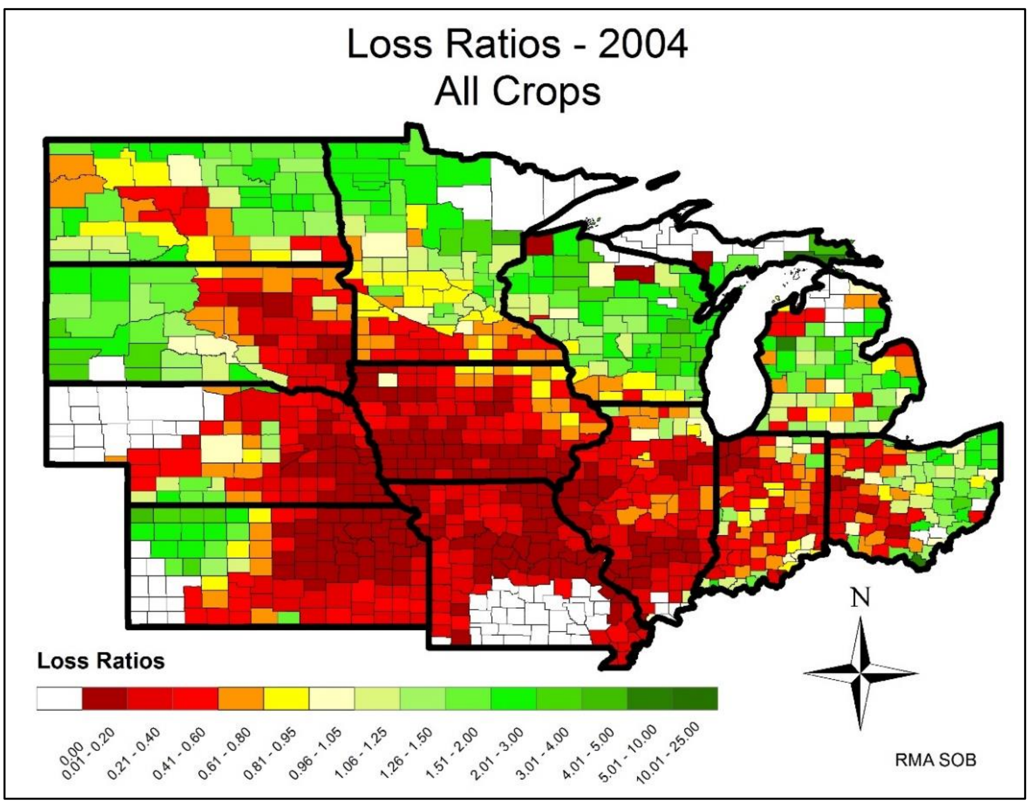
A8:


Loss Ratios - 2002
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

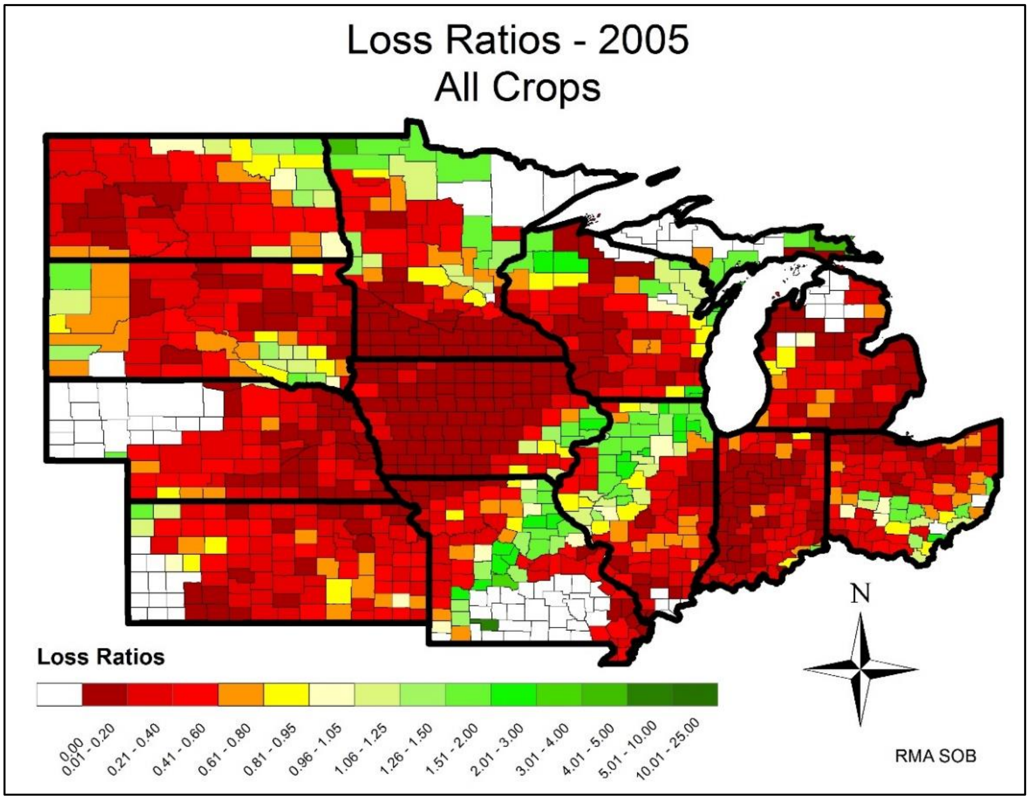
A9:


Loss Ratios - 2003
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

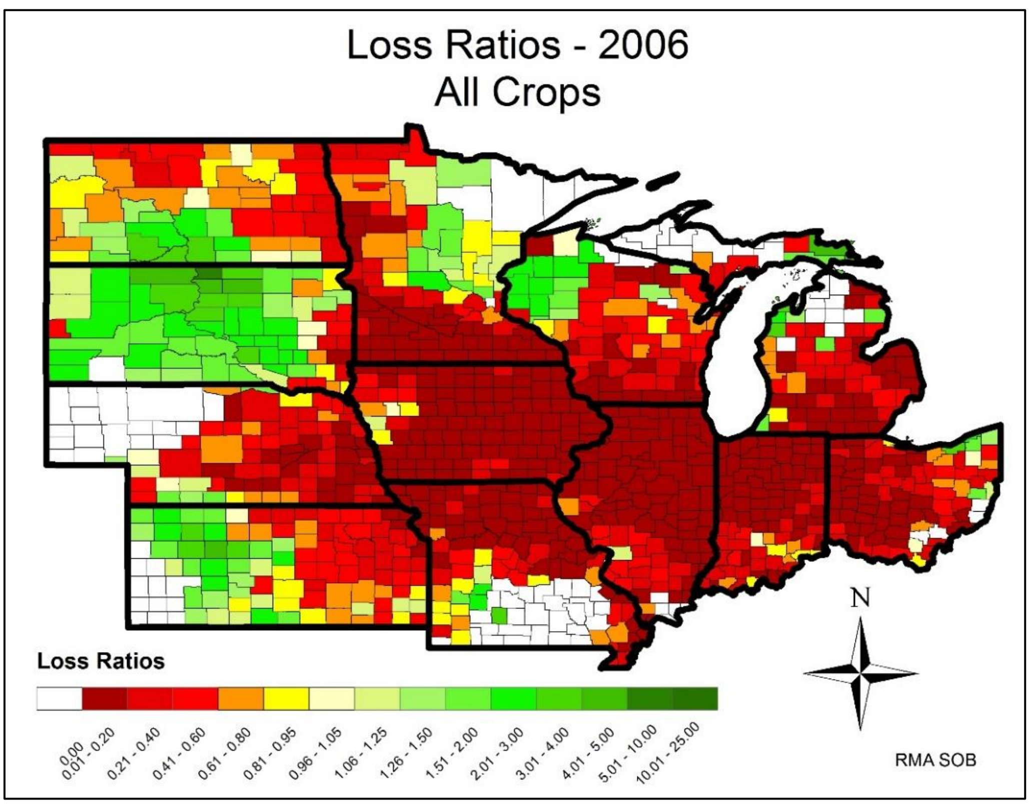
A10:


Loss Ratios - 2004
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

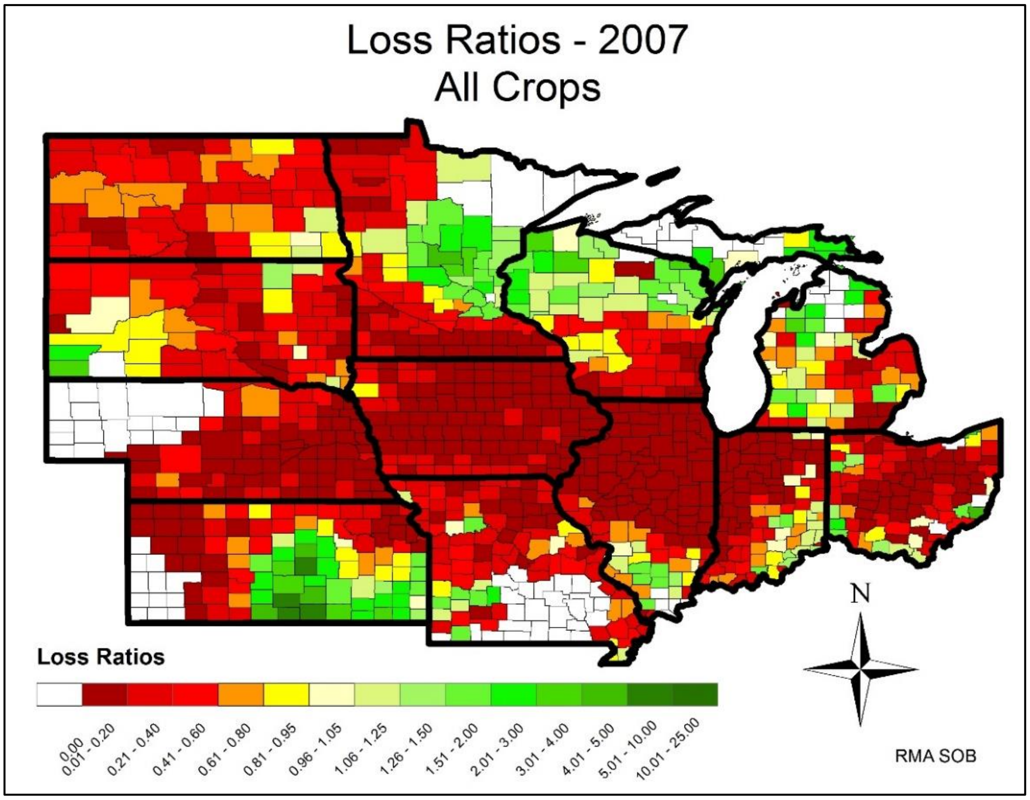
A11:


Loss Ratios - 2005
All Crops
N
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
RMA SOB

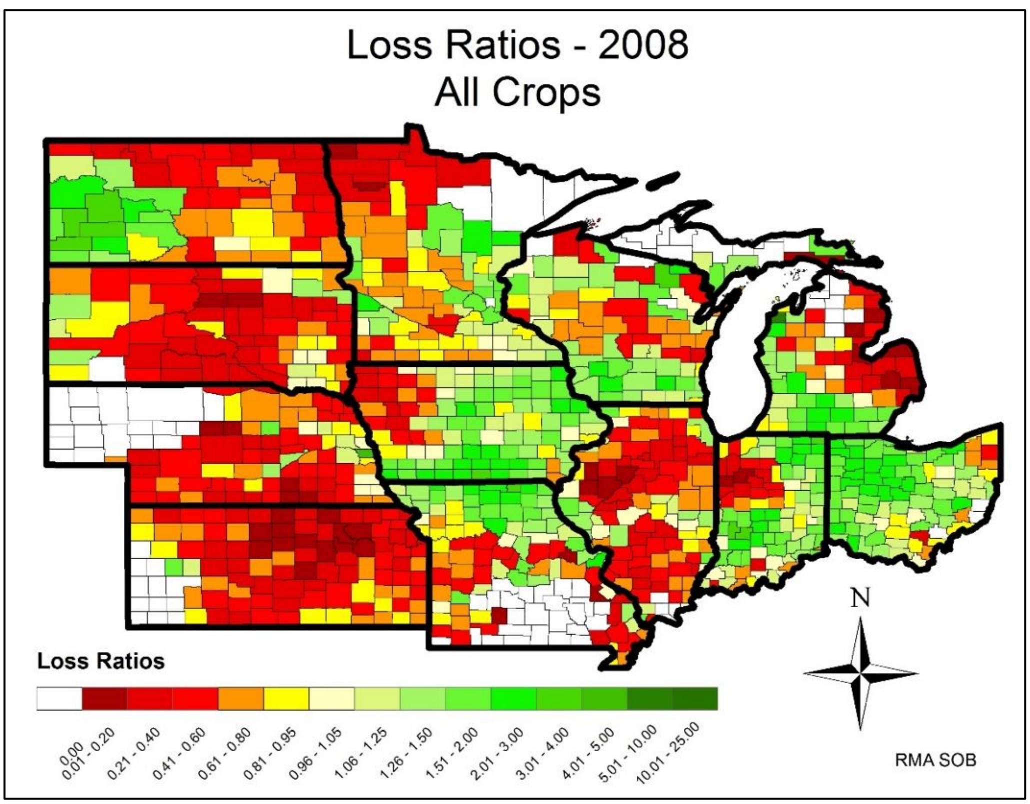
A12:


Loss Ratios - 2006
All Crops
N
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
RMA SOB

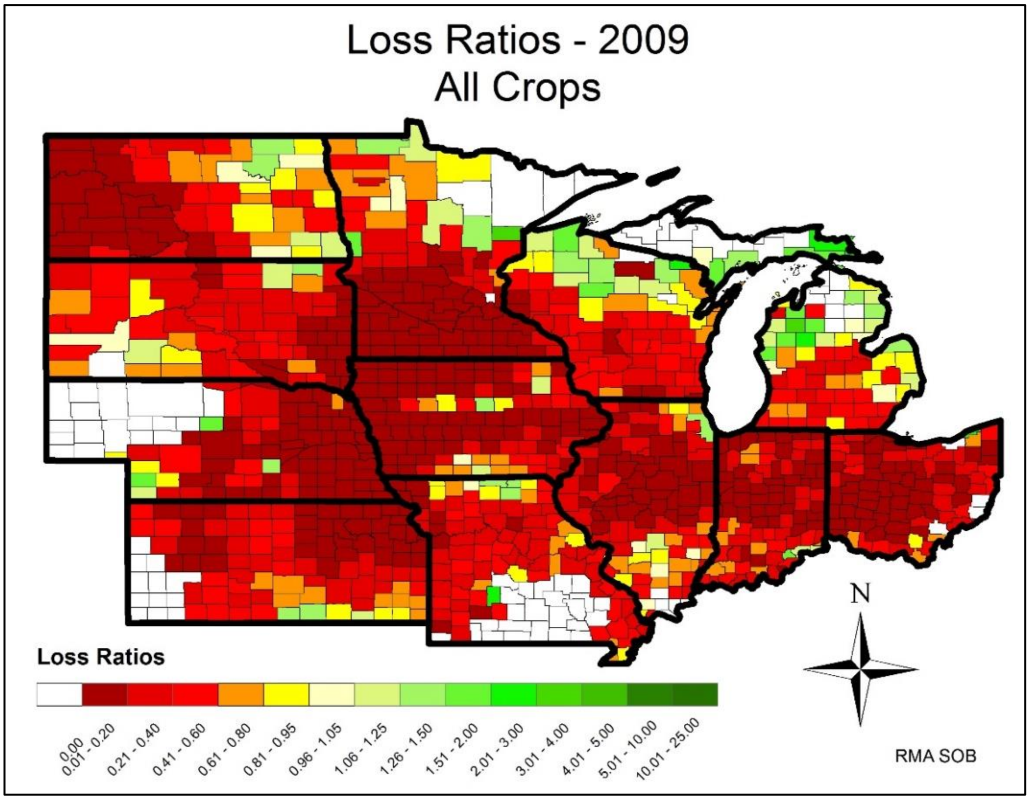
A13:


Loss Ratios - 2007
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

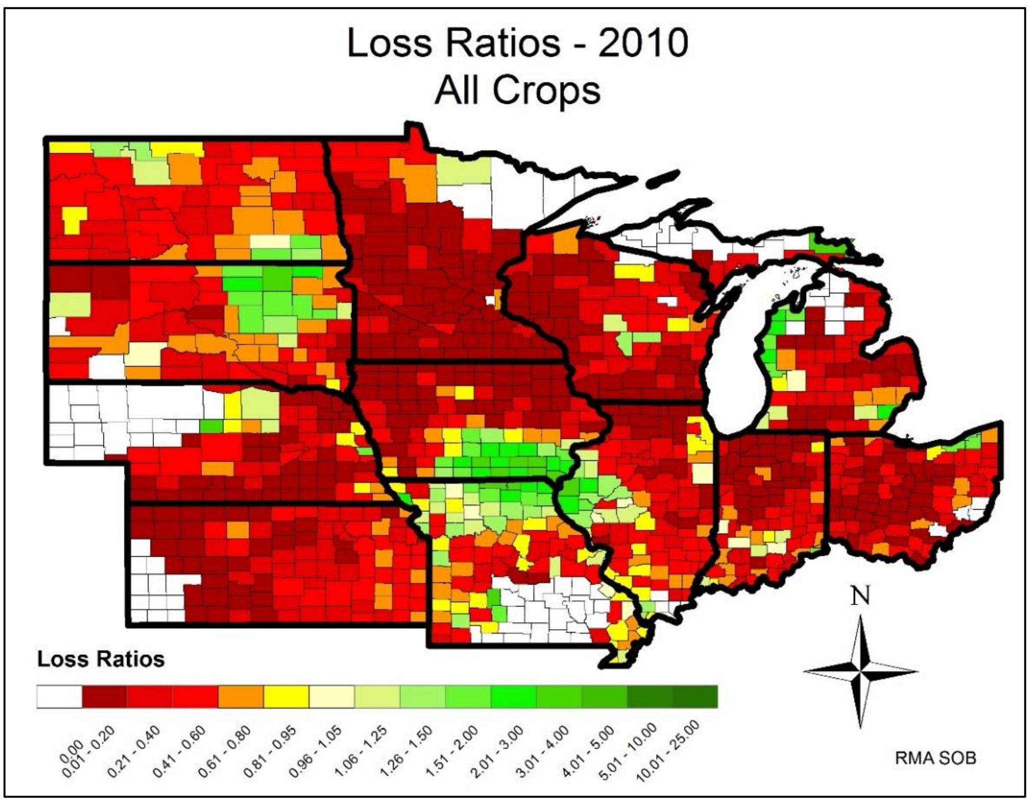
A14:


Loss Ratios - 2008
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

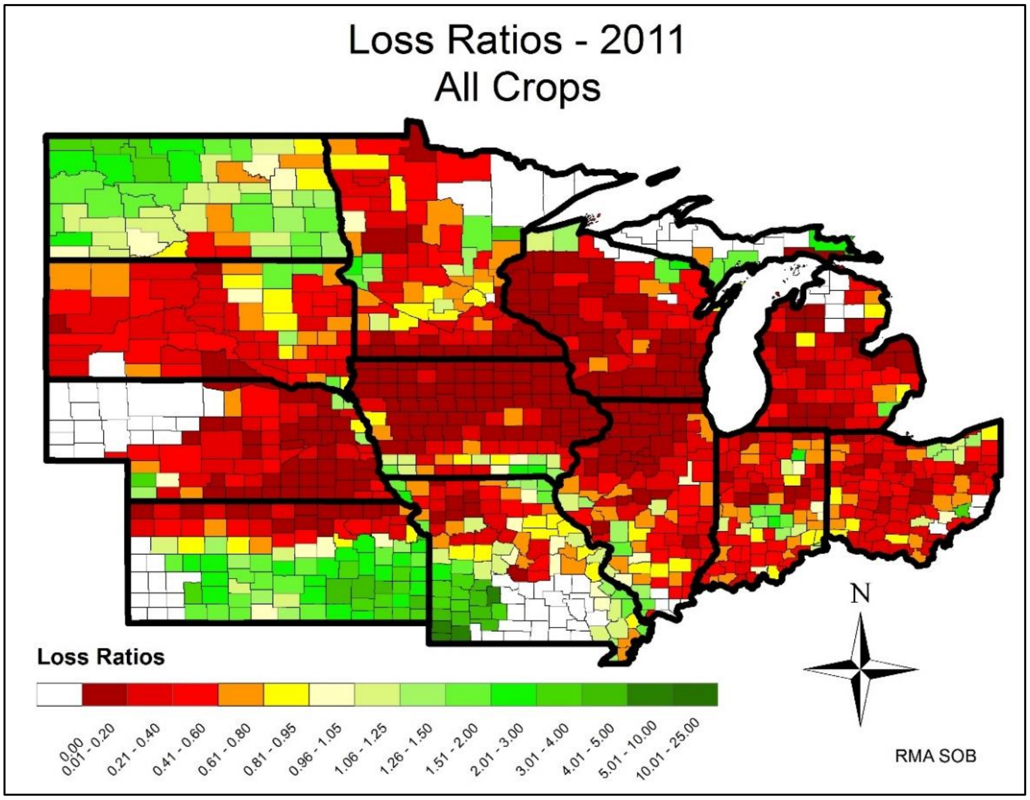
A15:


Loss Ratios - 2009
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

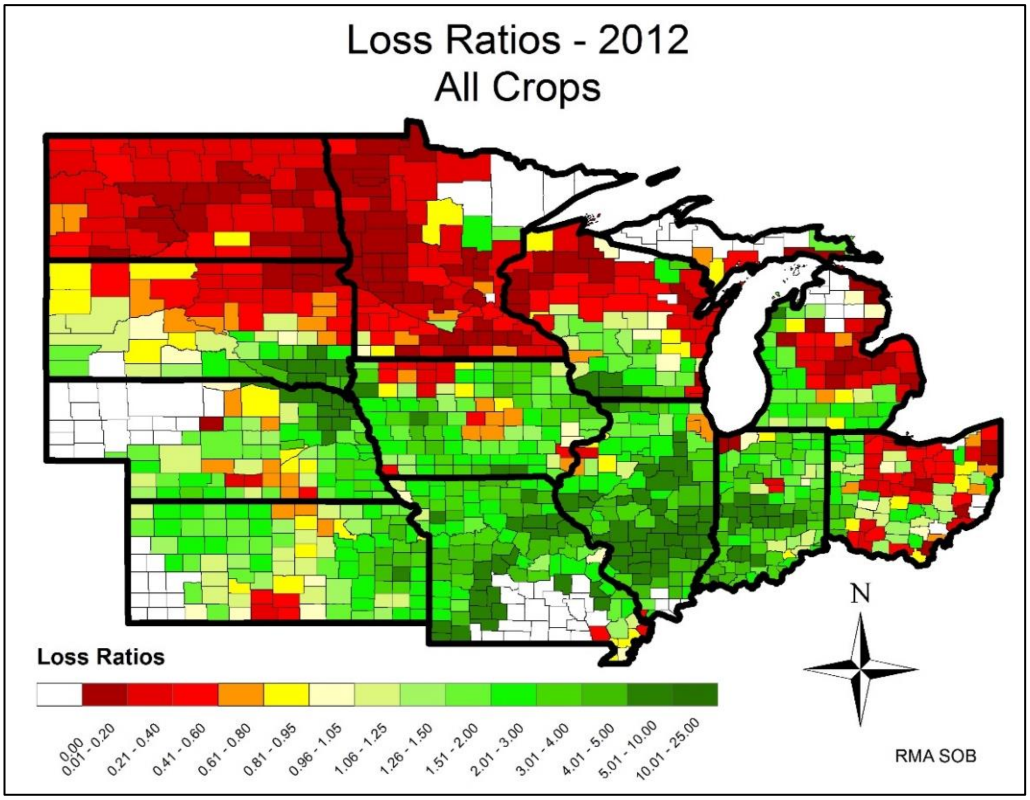
A16:


Loss Ratios - 2010
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

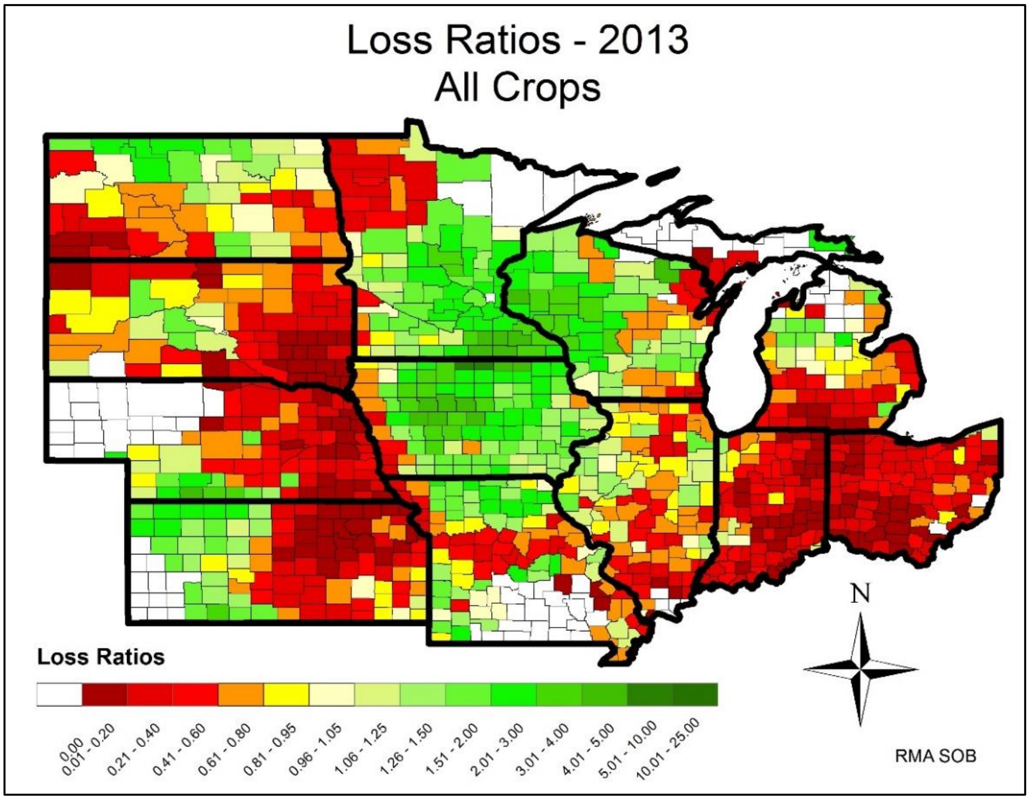
A17:


Loss Ratios - 2011
All Crops
N
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
RMA SOB

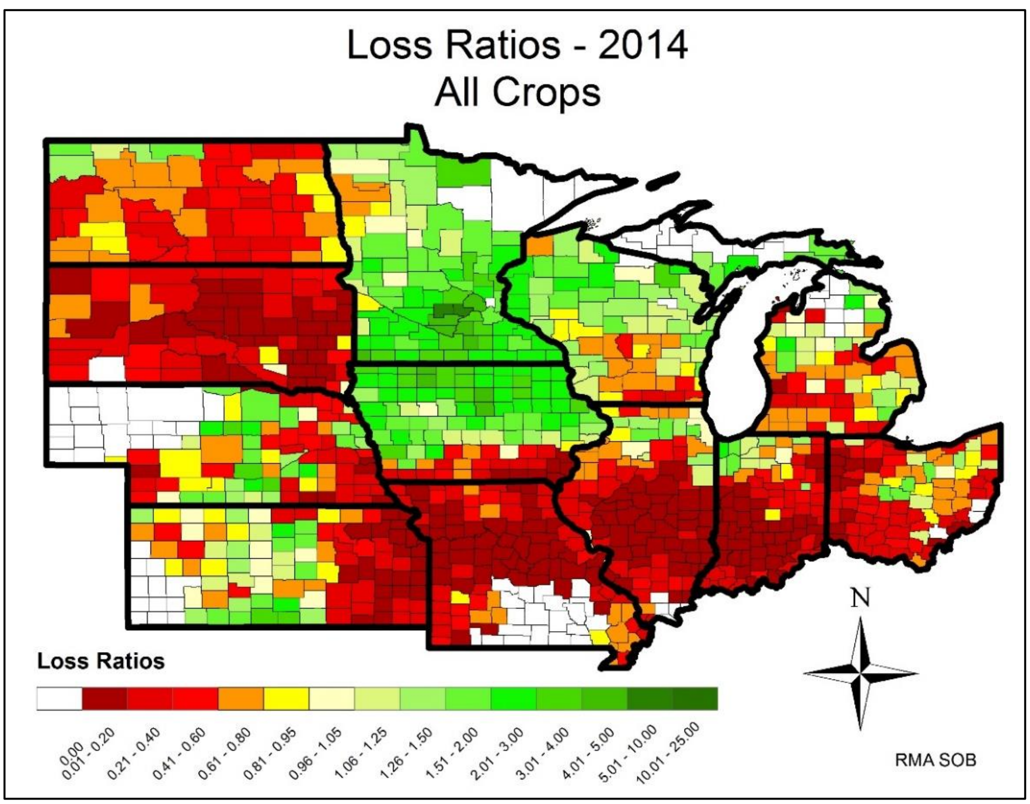
A18:


Loss Ratios - 2012
All Crops
N
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
RMA SOB

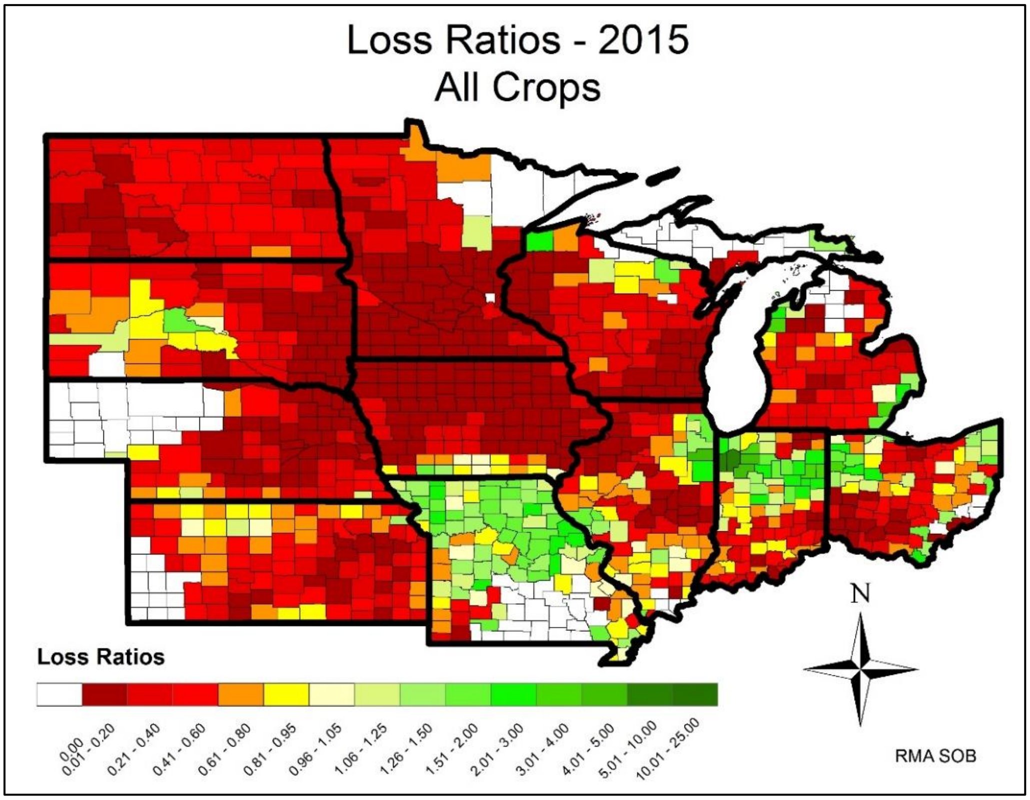
A19:


Loss Ratios - 2013
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

A20:

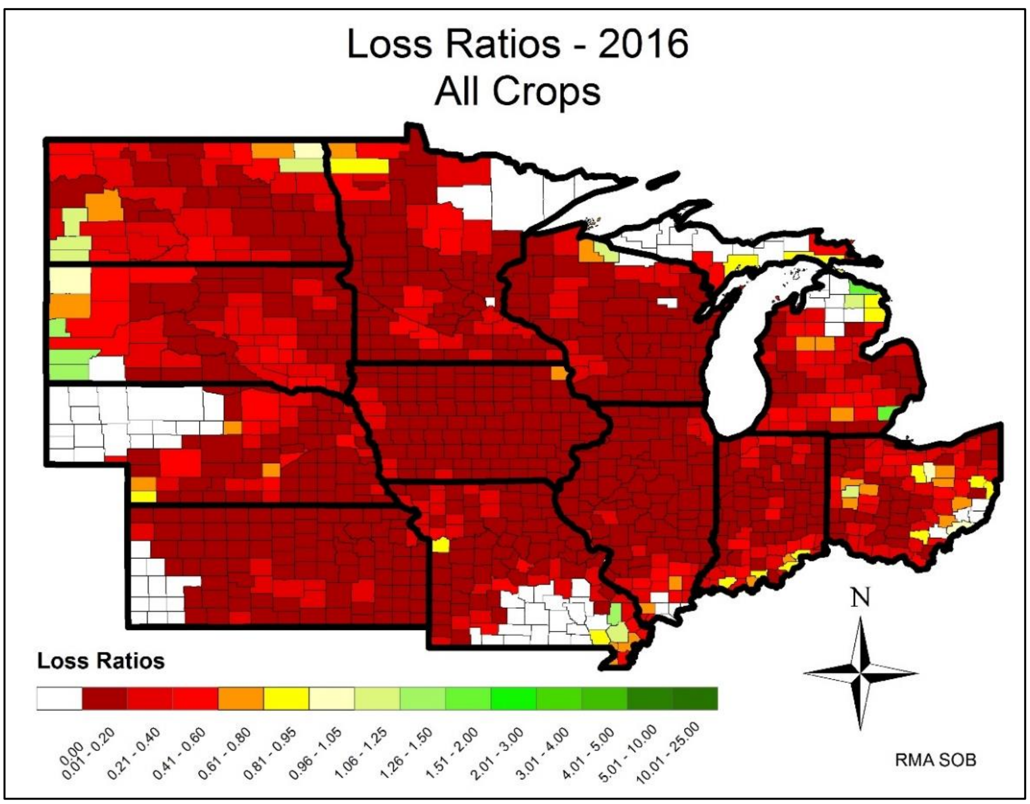

Loss Ratios - 2014
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

A21:



Loss Ratios - 2015
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

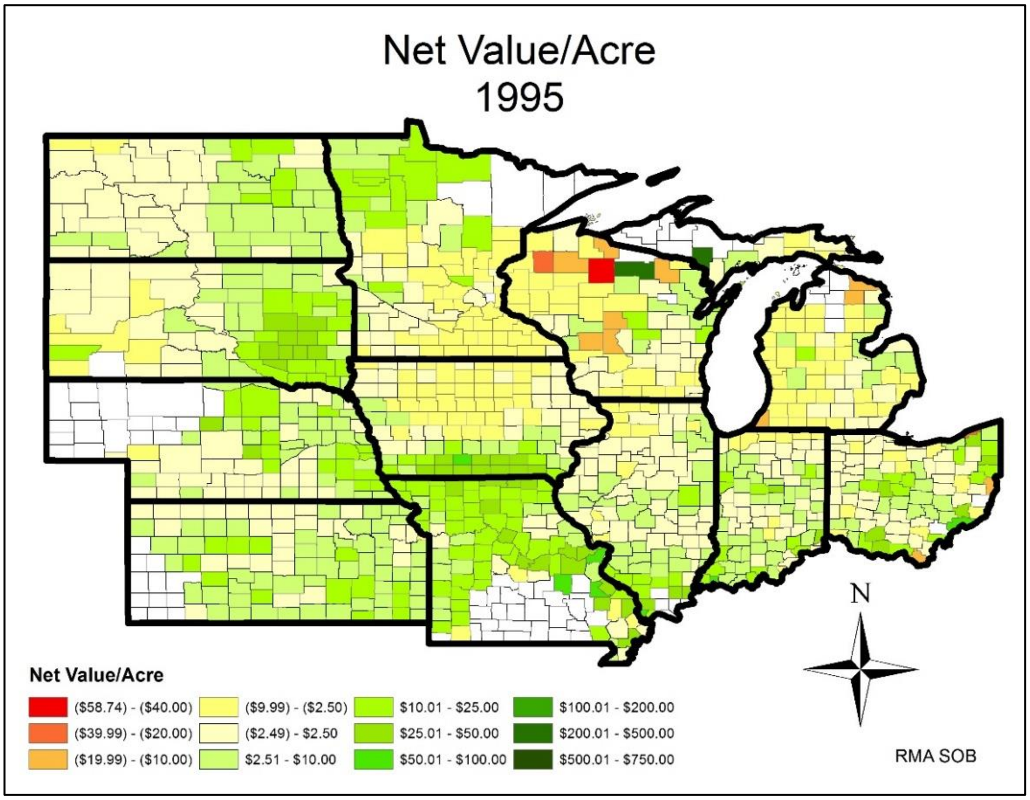
A22:



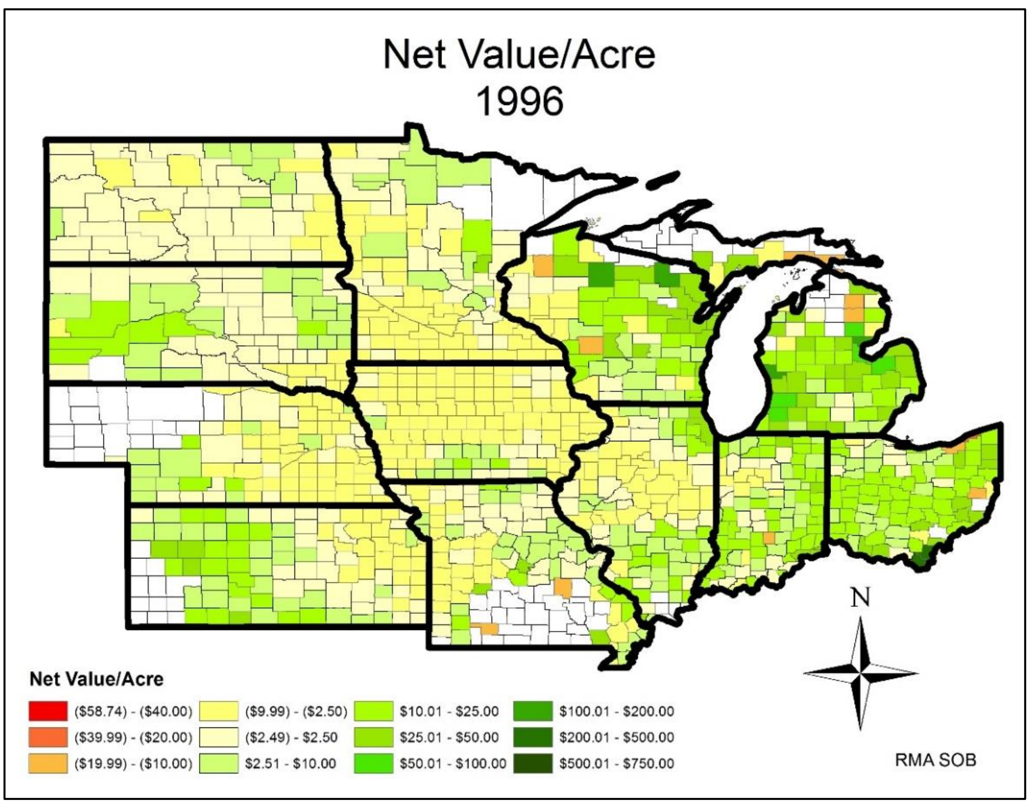
Loss Ratios - 2016
All Crops
Loss Ratios
0.00
0.01 - 0.20
0.21 - 0.40
0.41 - 0.60
0.61 - 0.80
0.81 - 0.95
0.96 - 1.05
1.06 - 1.25
1.26 - 1.50
1.51 - 2.00
2.01 - 3.00
3.01 - 4.00
4.01 - 5.00
5.01 - 10.00
10.01 - 25.00
N
RMA SOB

APPENDIX B: NET VALUE FROM CROP INSURANCE MAPS

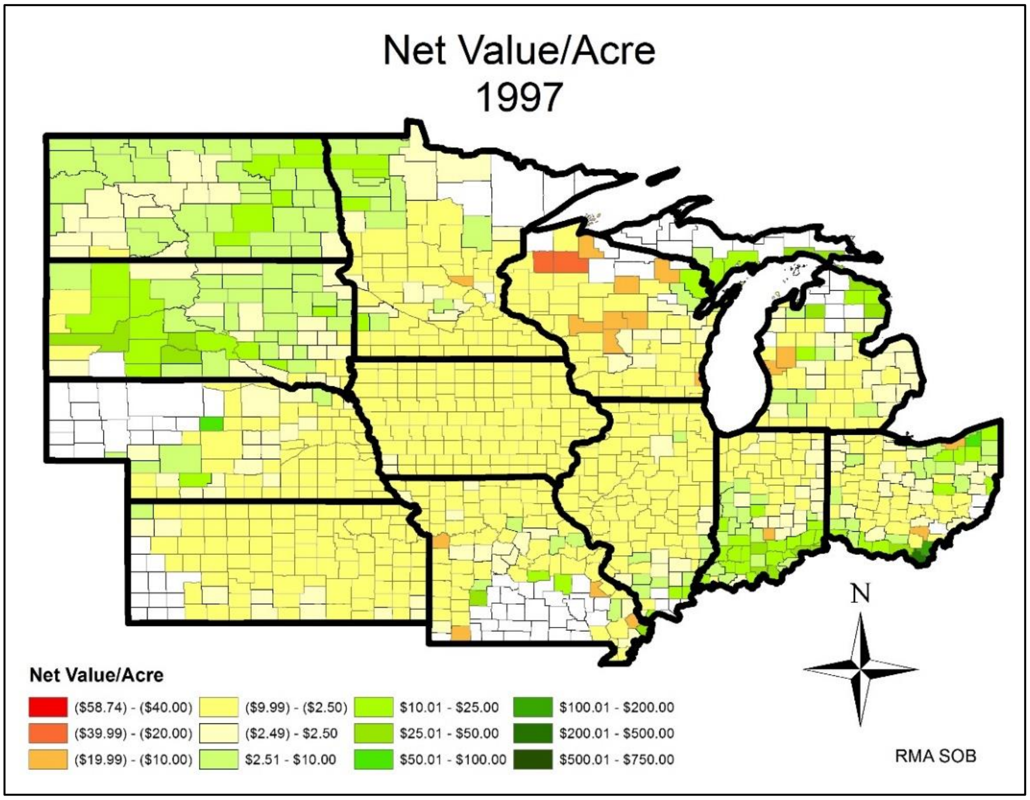
B1:



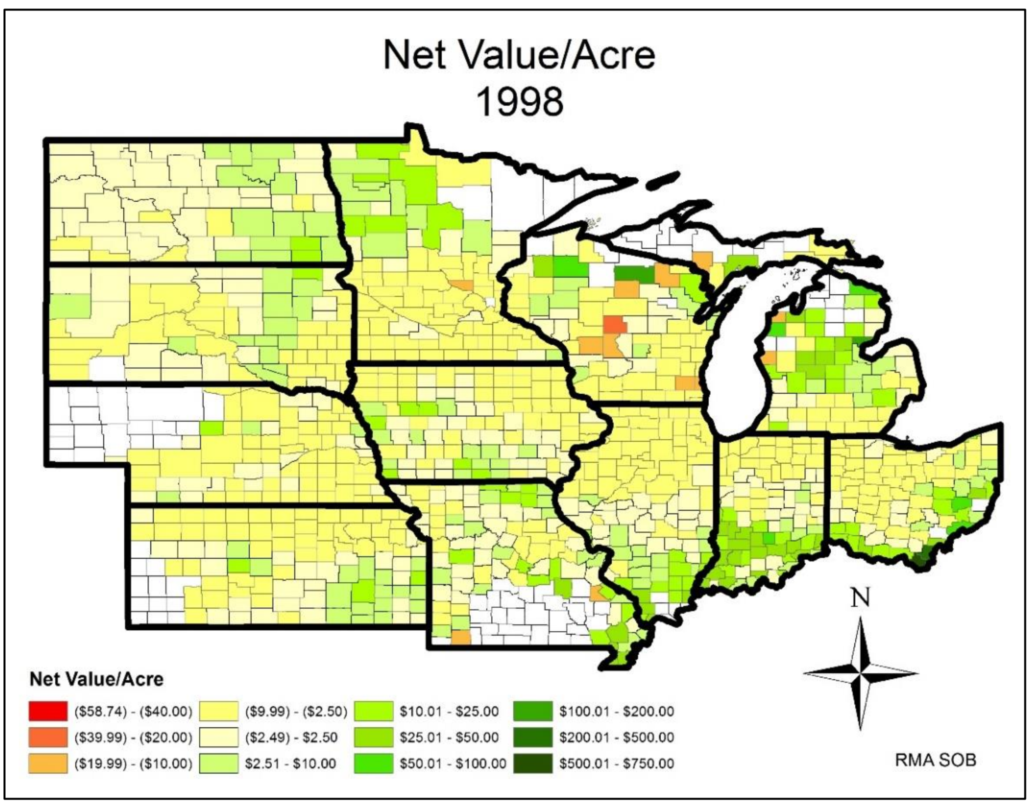
B2:



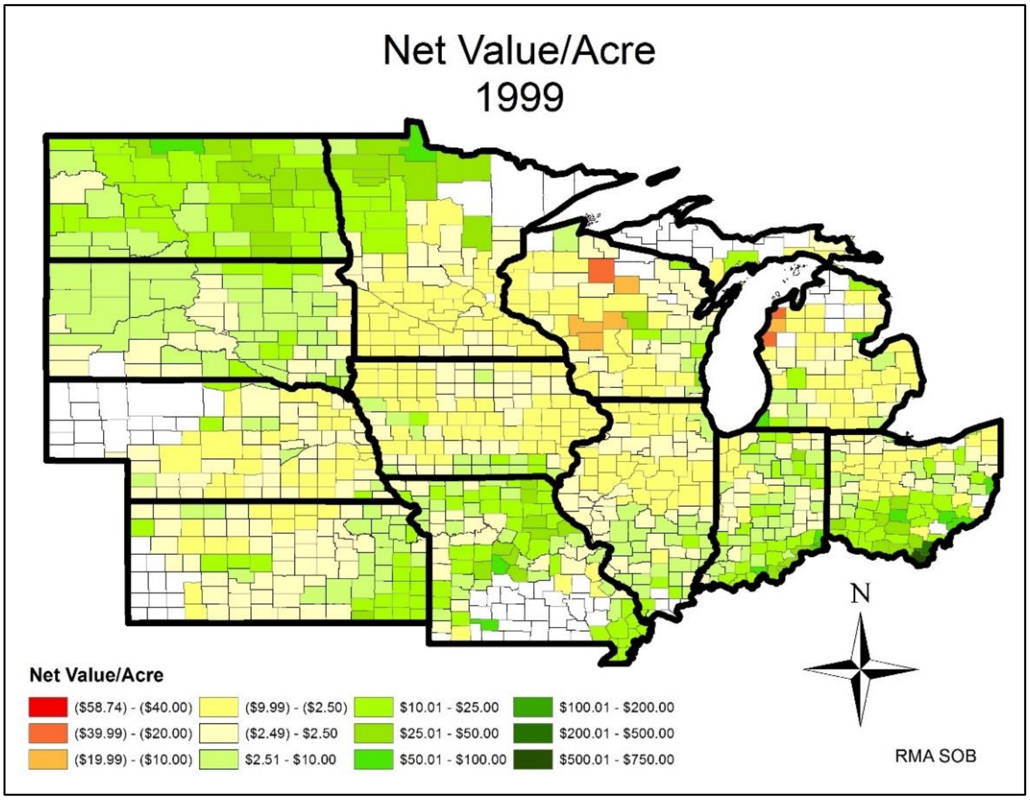
B3:


Net Value/Acre
1997
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

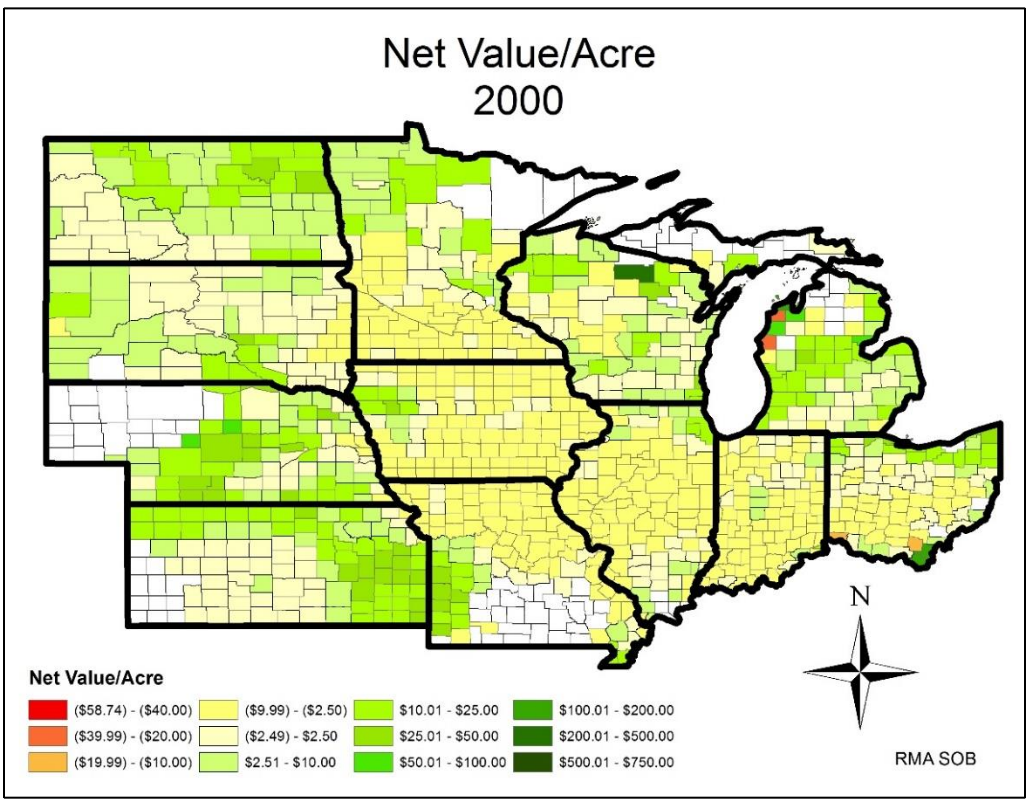
B4:


Net Value/Acre
1998
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

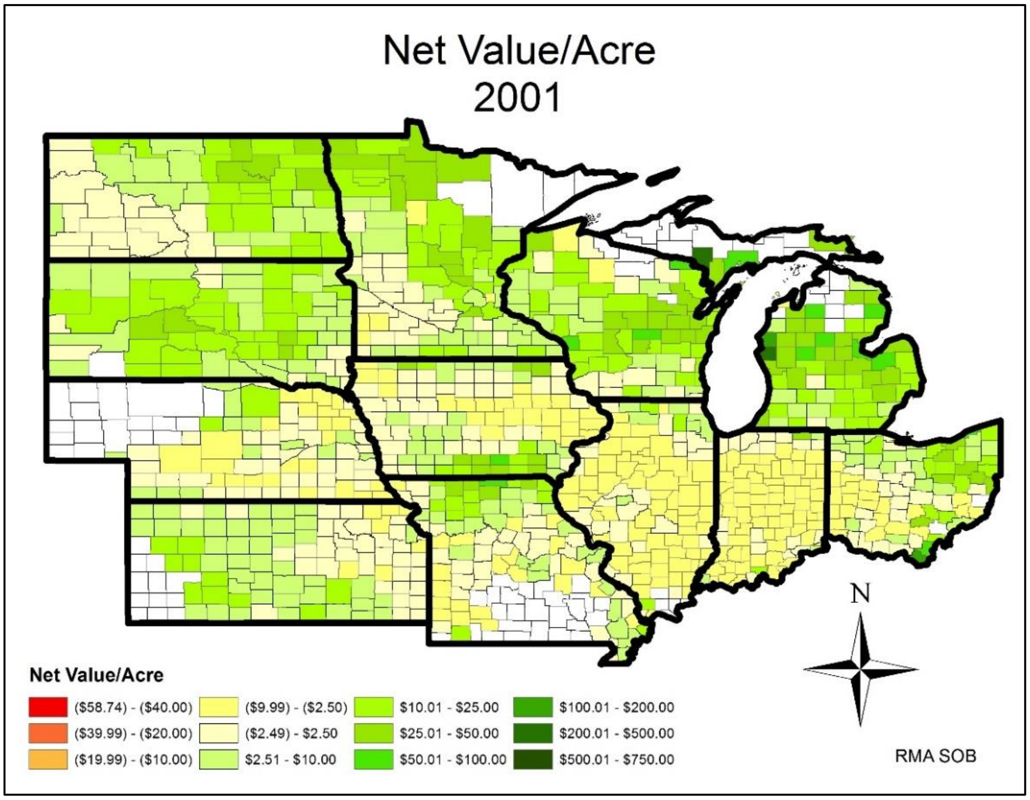
B5:


Net Value/Acre
1999
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

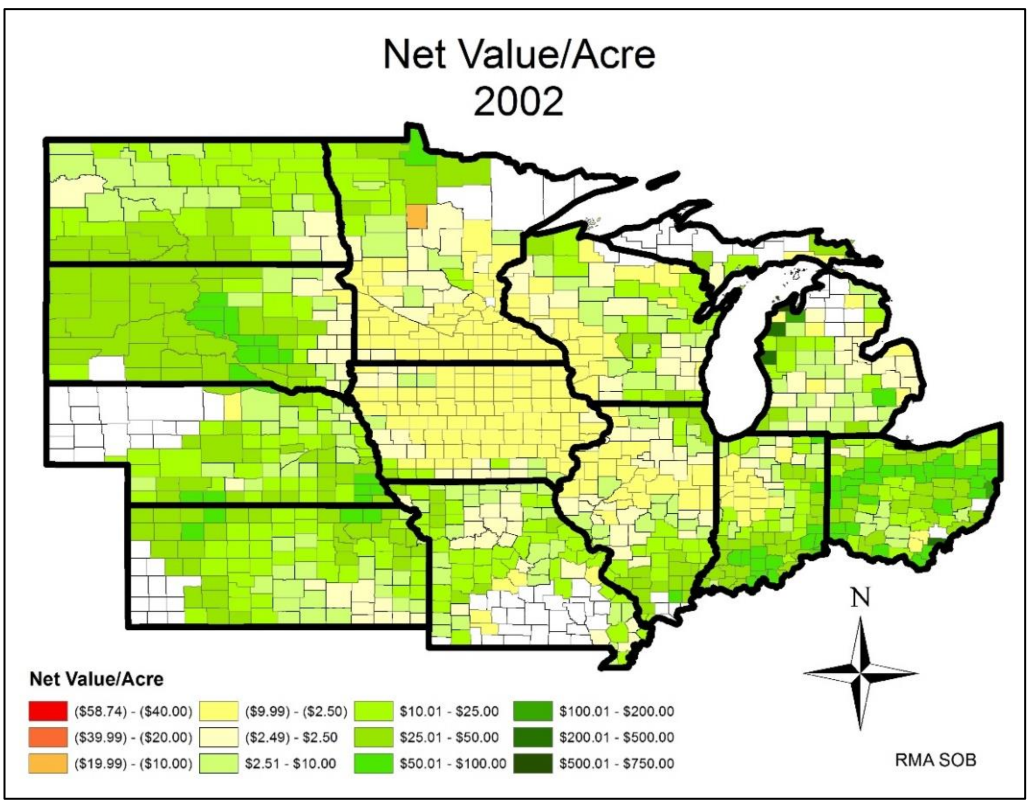
B6:


Net Value/Acre
2000
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

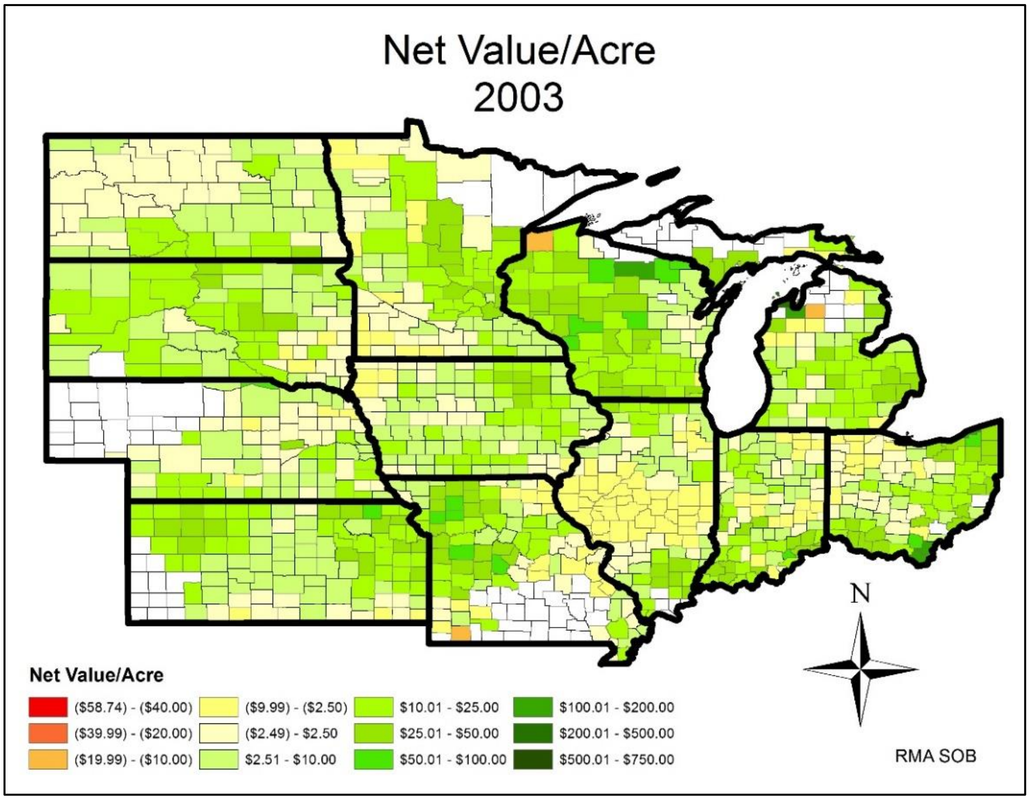
B7:


Net Value/Acre
2001
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

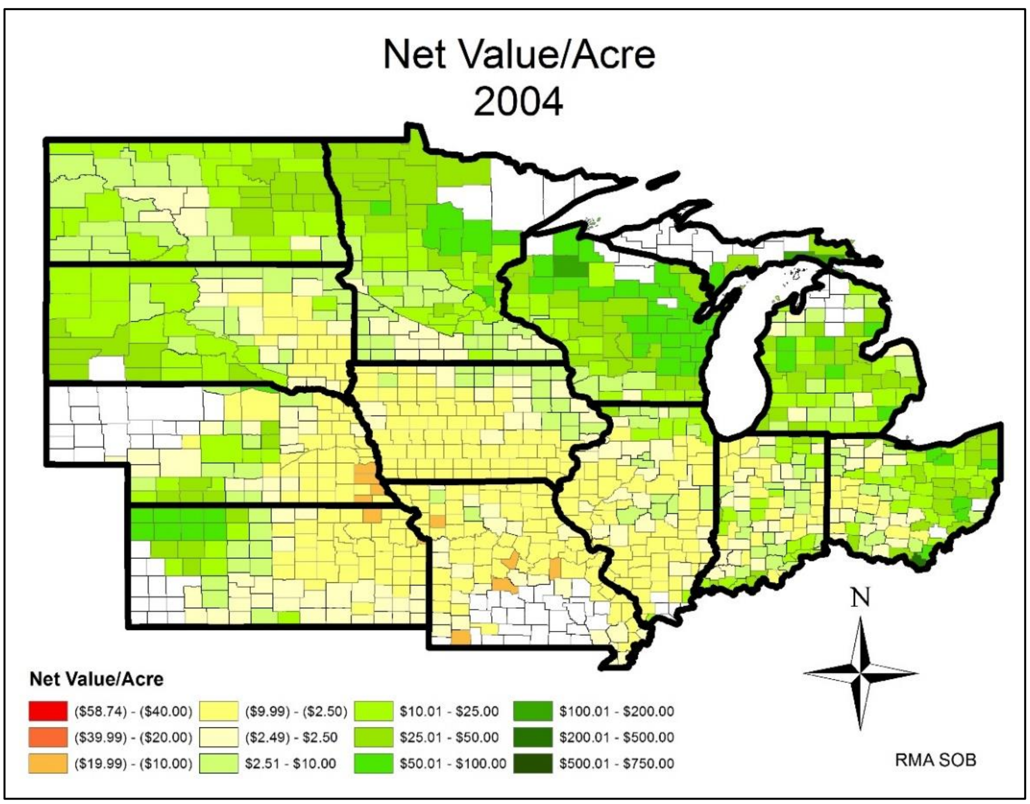
B8:


Net Value/Acre
2002
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

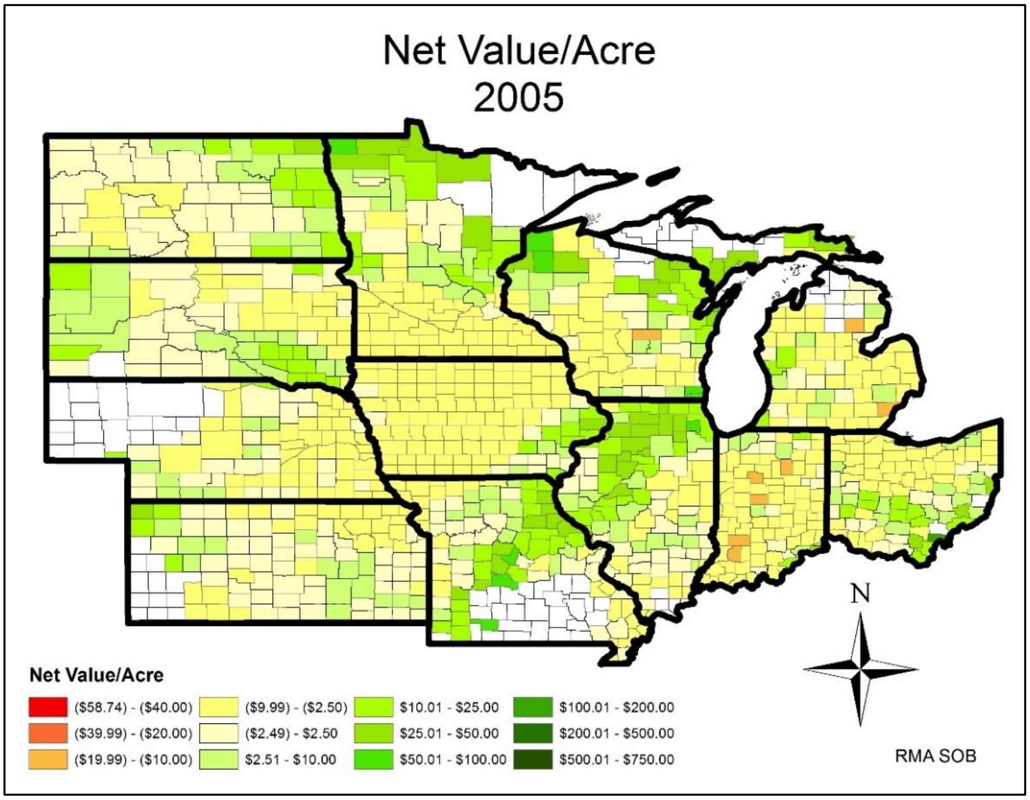
B9:


Net Value/Acre
2003
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

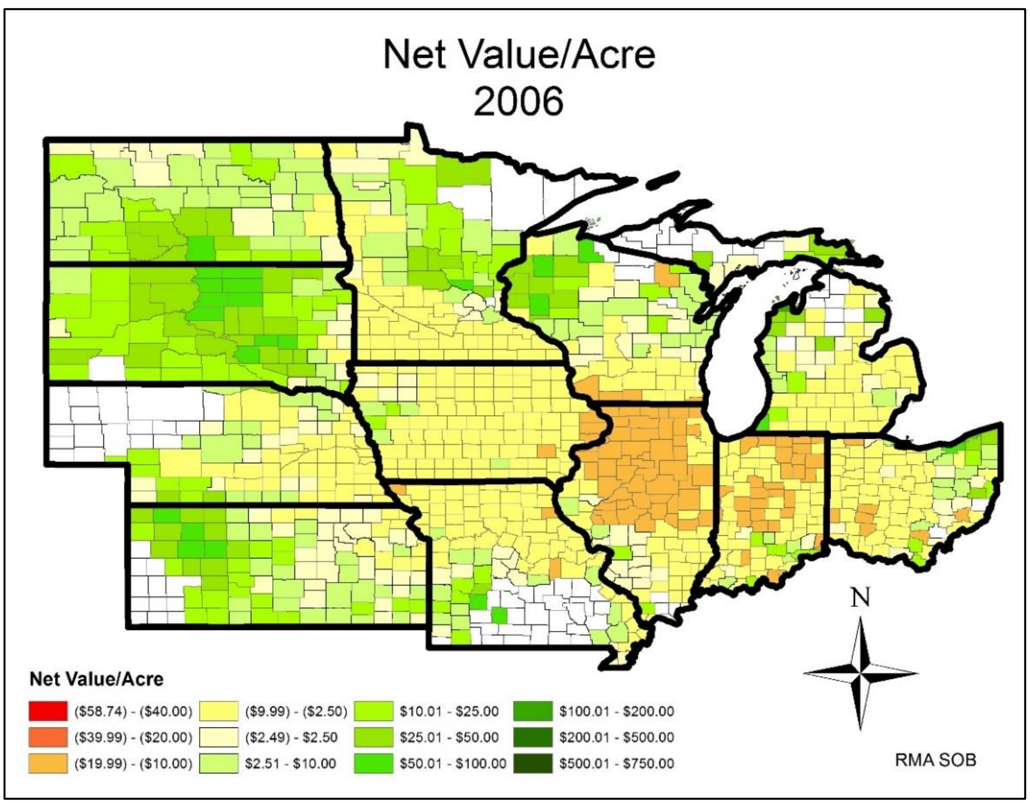
B10:


Net Value/Acre
2004
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

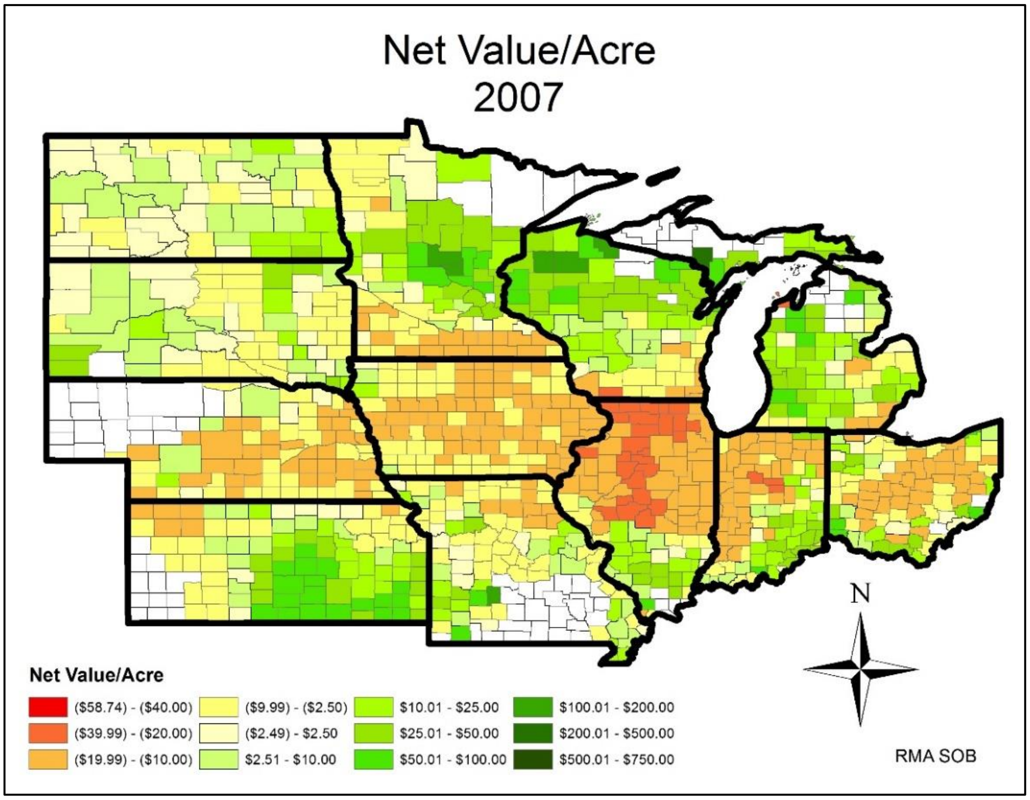
B11:


Net Value/Acre
2005
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

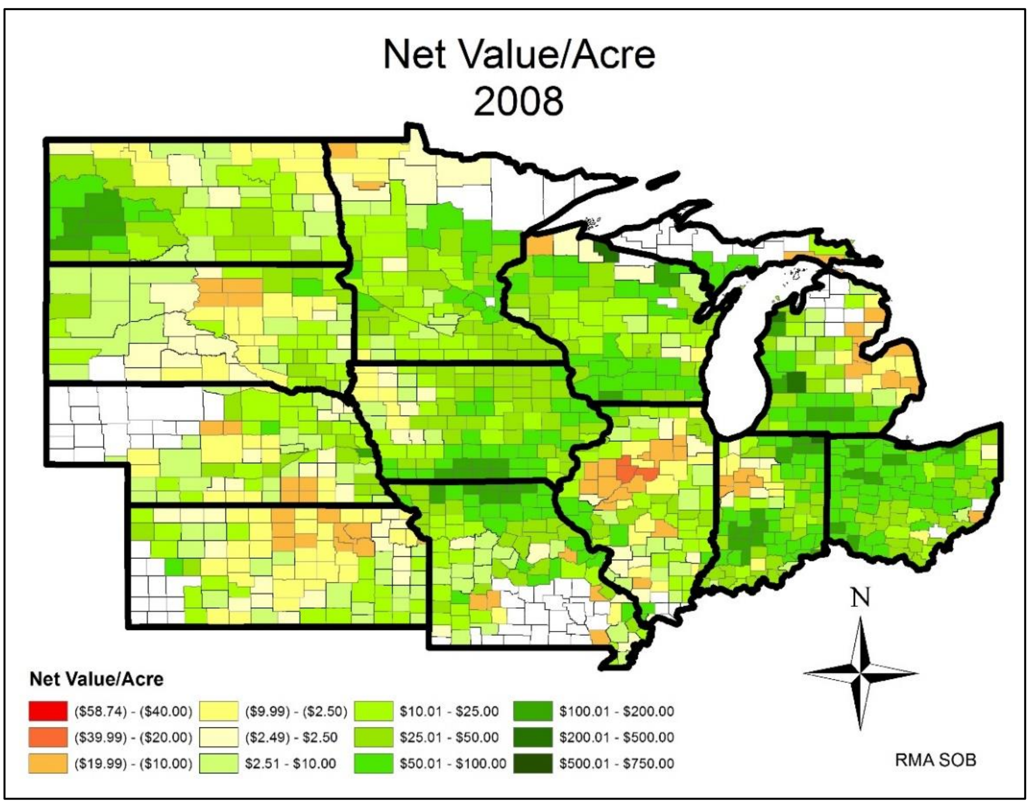
B12:


Net Value/Acre
2006
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

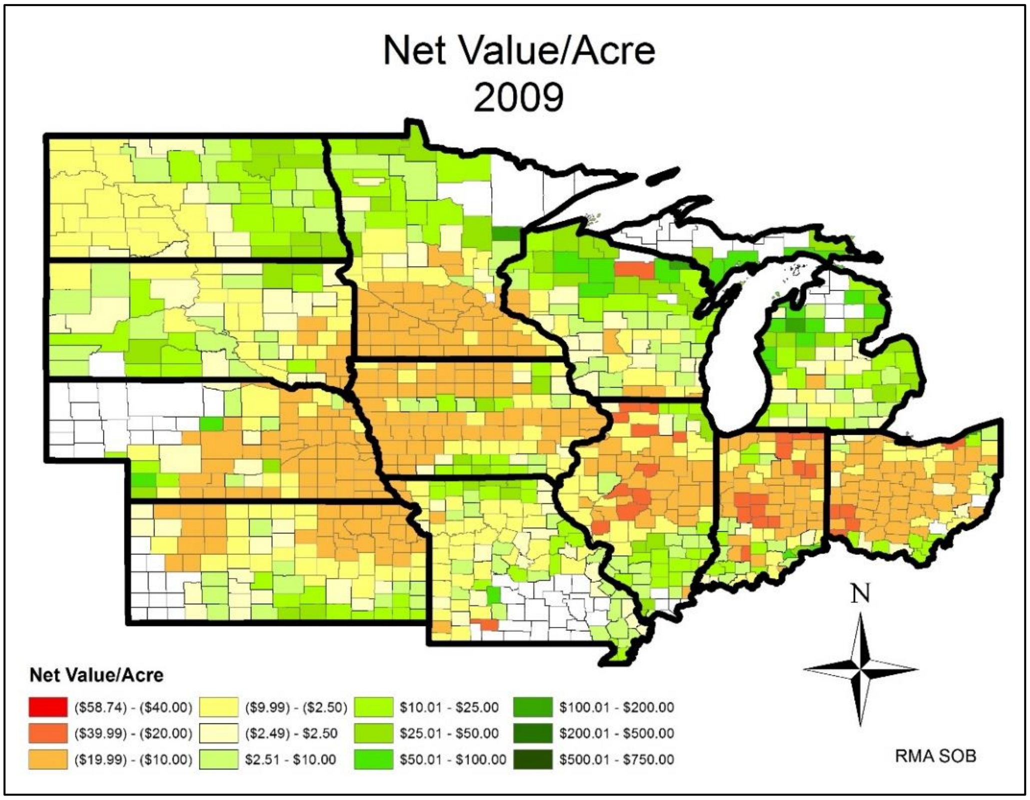
B13:


Net Value/Acre
2007
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

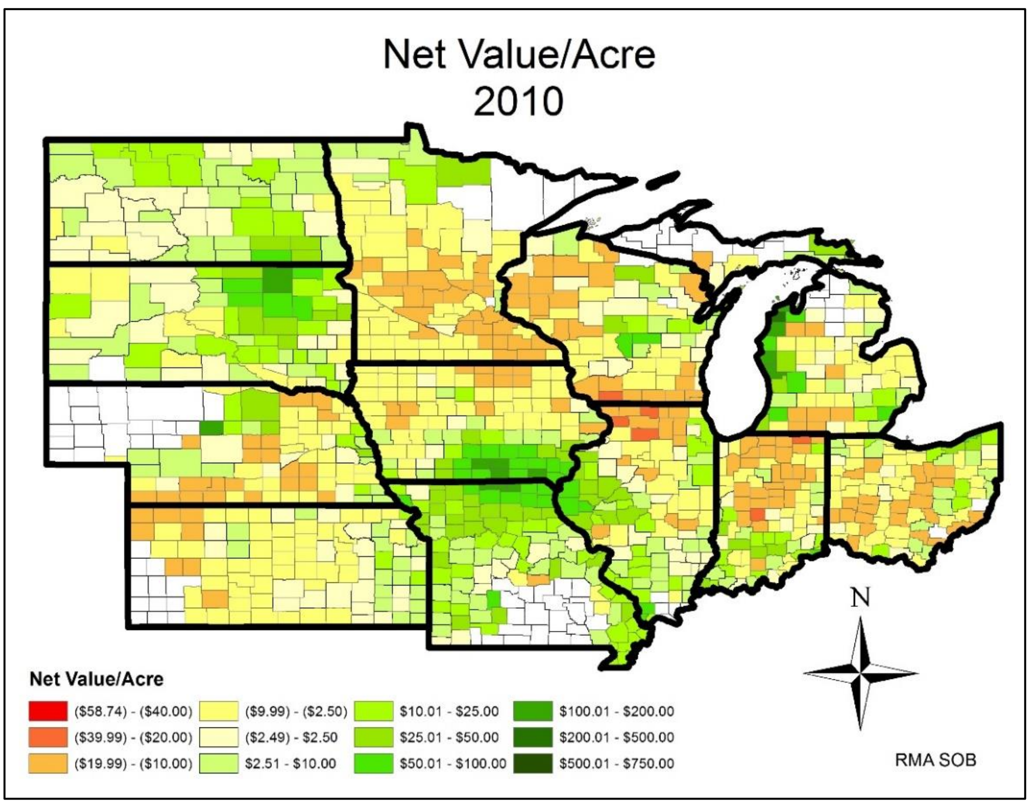
B14:


Net Value/Acre
2008
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

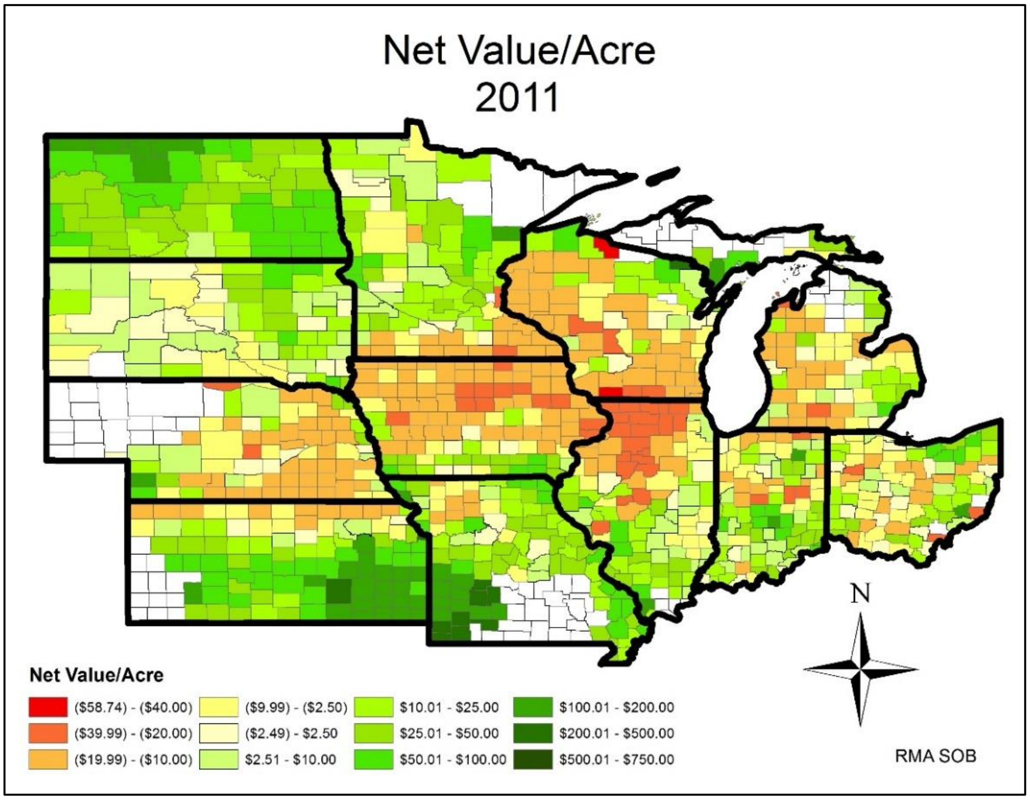
B15:


Net Value/Acre
2009
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

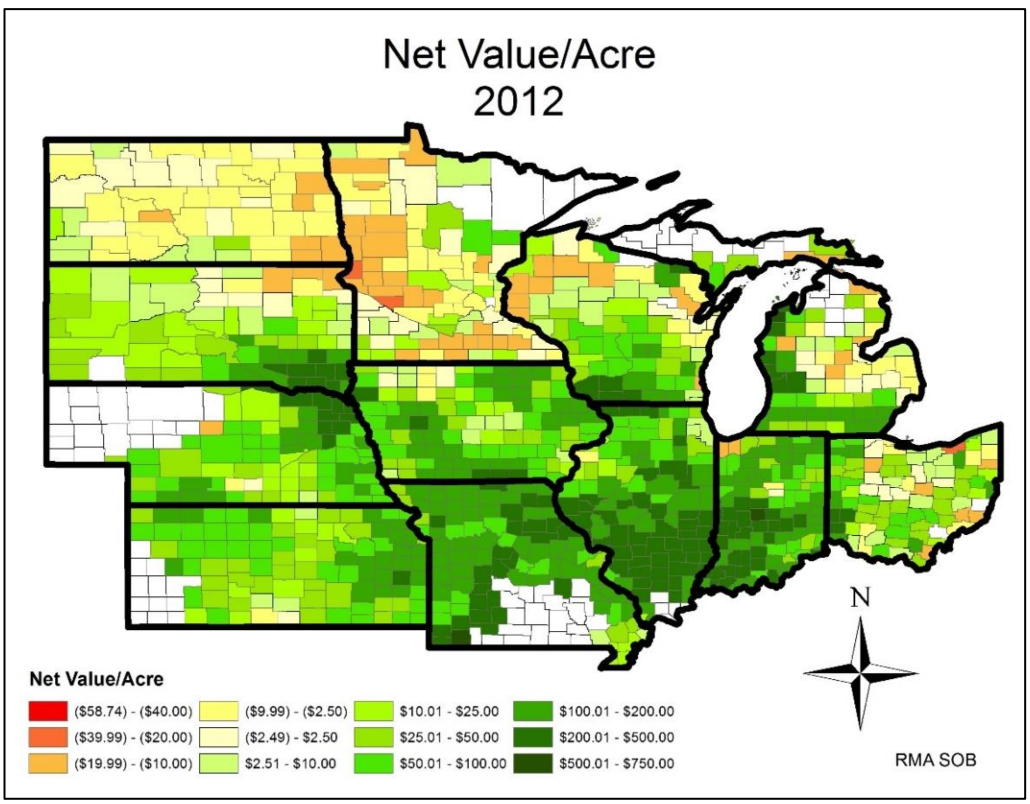
B16:


Net Value/Acre
2010
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

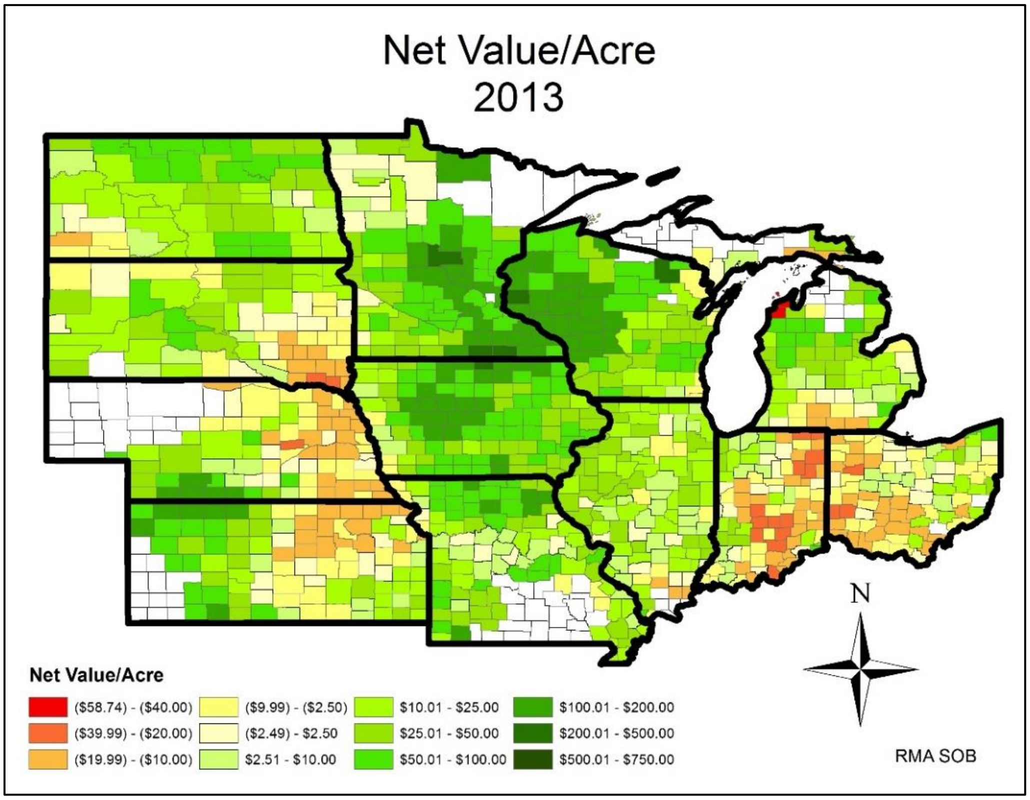
B17:


Net Value/Acre
2011
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

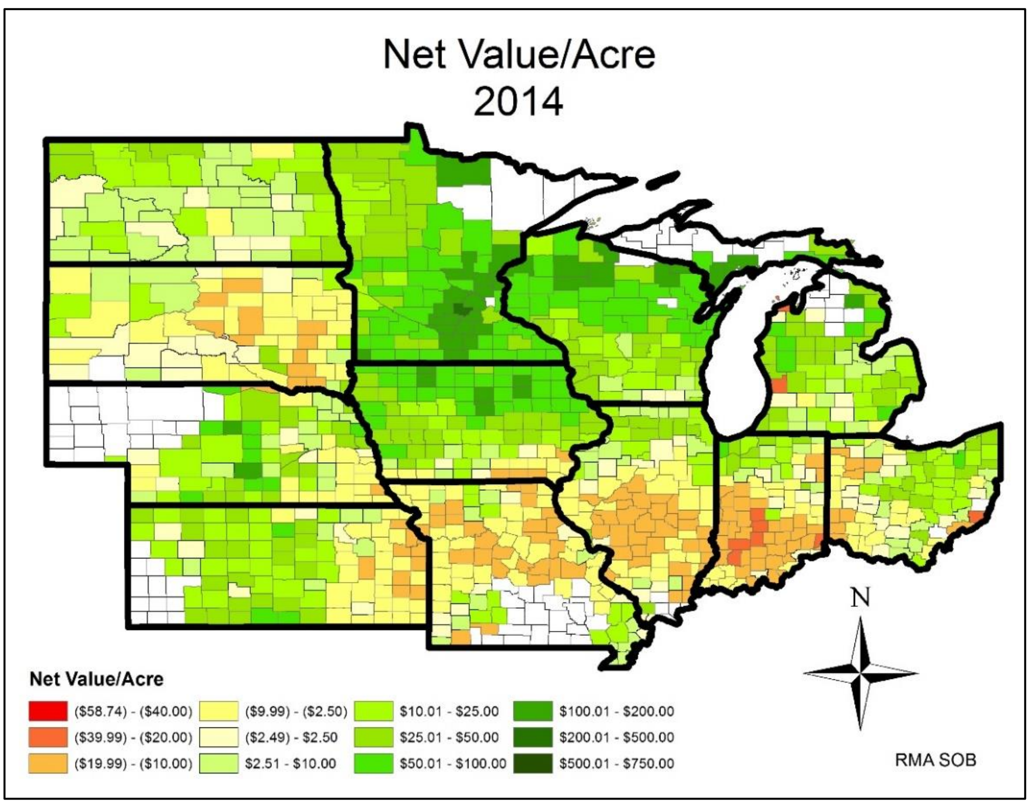
B18:


Net Value/Acre
2012
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

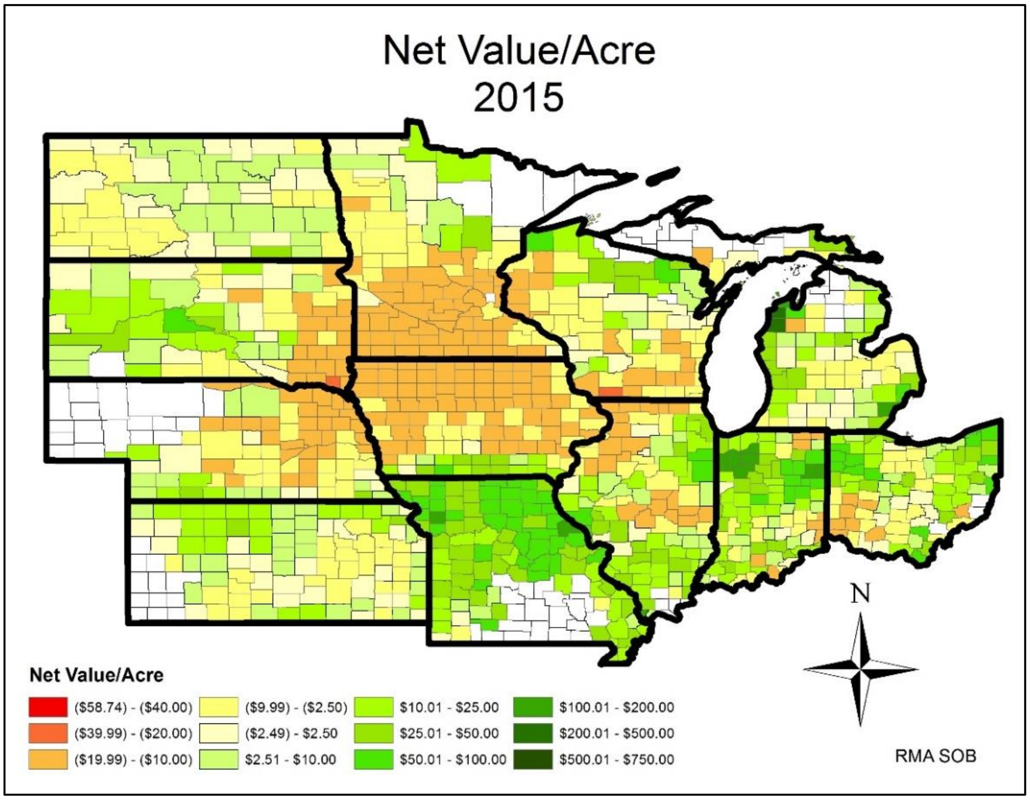
B19:


Net Value/Acre
2013
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

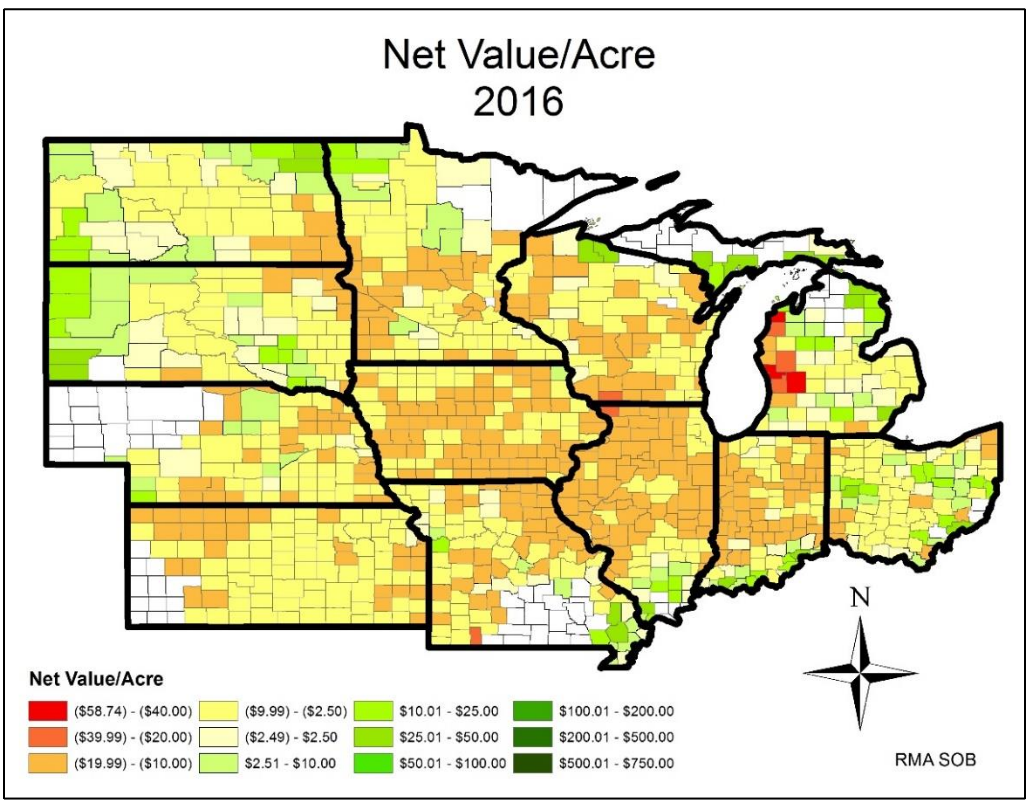
B20:


Net Value/Acre
2014
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

B21:


Net Value/Acre
2015
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB

B22:


Net Value/Acre
2016
N
Net Value/Acre
($58.74) - ($40.00)
($39.99) - ($20.00)
($19.99) - ($10.00)
($9.99) - ($2.50)
($2.49) - $2.50
$2.51 - $10.00
$10.01 - $25.00
$25.01 - $50.00
$50.01 - $100.00
$100.01 - $200.00
$200.01 - $500.00
$500.01 - $750.00
RMA SOB