THE IMPACT OF CLOUD SEEDING ON SMALL GRAIN CROPS: EVIDENCE FROM THE NORTH DAKOTA CLOUD MODIFICATION PROJECT

By

Scott Knowles

A THESIS

Submitted to
Michigan State University
in partial fulfillment of the requirements
for the degree of

Agricultural, Food, and Resource Economics – Master of Science

2020

ABSTRACT

THE IMPACT OF CLOUD SEEDING ON SMALL GRAIN CROPS:
EVIDENCE FROM THE NORTH DAKOTA CLOUD MODIFICATION PROJECT

By

Scott Knowles

The North Dakota Cloud Modification Project (NDCMP) was established in 1951 to reduce severe hail damage and increase precipitation in specific counties in North Dakota. Annually, every June through August, participating counties receive cloud seeding treatment. Although some atmospheric studies have examined the efficacy of the treatment, few have used statistical procedures to determine how the program has affected crop yields and crop losses. I use the panel nature of historical cloud seeding participation and crop data to facilitate a two-way fixed effects regression framework with county-specific time trends to estimate the effect of cloud seeding on wheat and barley yields. In addition, I use federal crop insurance data to estimate the effect of cloud seeding on losses for those same crops. My evaluation indicates that the cloud seeding program had significant positive effects on crop yields and improved loss ratios.

ACKNOWLEDGEMENTS

Upon reflection of my time spent at Michigan State University, I feel that my research has been greatly improved upon by interactions with many colleagues. To all those who I fail to mention in this section, but with whom I have shared inspiring times, thank you.

This master's thesis would have never been written without the guidance of my mentor and advisor, Dr. Mark Skidmore. His eagerness to explore uncharted territories, and ongoing support of my academic growth are appreciated beyond words. I also thank Dr. Scott Swinton, Dr. Frank Lupi, and Dr. David Hennessy for their constructive feedback as part of my thesis committee. Additionally, I thank Yuyuan Che for sharing her approach to generating growing degree days, stress degree days, and moisture stress variables.

Special thanks to Mark Schneider, Chief Meteorologist of the North Dakota Atmospheric Resource Board, and president-elect of the Weather Modification Association. His program participation data made the statistical analyses possible, and his comments shed much light on the topic under study.

For supplying additional data, I thank the National Oceanic and Atmospheric Administration (NOAA) as well as the United States Department of Agriculture's (USDA) National Agricultural Statistics Service (NASS). Their respective employees were always helpful when I had questions about the data. Finally, thank you to Dr. Nicole Mason-Wardell, Dr. Maria Porter, and Dr. Jeff Wooldridge for educating me about statistics and econometrics.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

1.1 Background and Motivation

The oldest, and most heavily studied cloud seeding program in the *world* is the North Dakota Cloud Modification Project (NDCMP) in the United States. With origins dating back to the early 1950s, the NDCMP has evolved over the years, but its objectives have remained consistent: reduce local damage incurred by summertime hailstorms and increase beneficial precipitation.

At first, only ground-based cloud seeding generators were used in a grassroots effort to protect crops in North Dakota. Later, with the founding of Weather Modification, Inc., aircraft were leveraged to introduce a cloud seeding agent (usually silver iodide) into potentially problematic storm clouds. In 1975, the North Dakota Weather Modification Board (later renamed the Atmospheric Resource Board) was established as a division of the Aeronautics Commission after promising results of exploratory cloud seeding studies were publicized (Butchbaker, 1970). Today the North Dakota Atmospheric Resource Board (NDARB) oversees the NDCMP.

Although precipitation enhancement is claimed to be beneficial to farmers in western North Dakota, managing hailstorms has continued to be the program's primary objective. In 2019, approximately 80 percent of airtime was spent seeding clouds with the goal of mitigating hail damage (Weather Modification International, 2019).

Initially, airborne cloud seeding operations were paid for individually by farmers and ranchers across the state. In 1976, county participation soared as a state cost-share initiative was introduced for the first time (see Figure 1). However, today only six out of fifty-three counties participate in the program. The high attrition rate might be partially explained by the fact that the eastern side of North Dakota receives more rainfall than the western side, on average (see Figure 2).

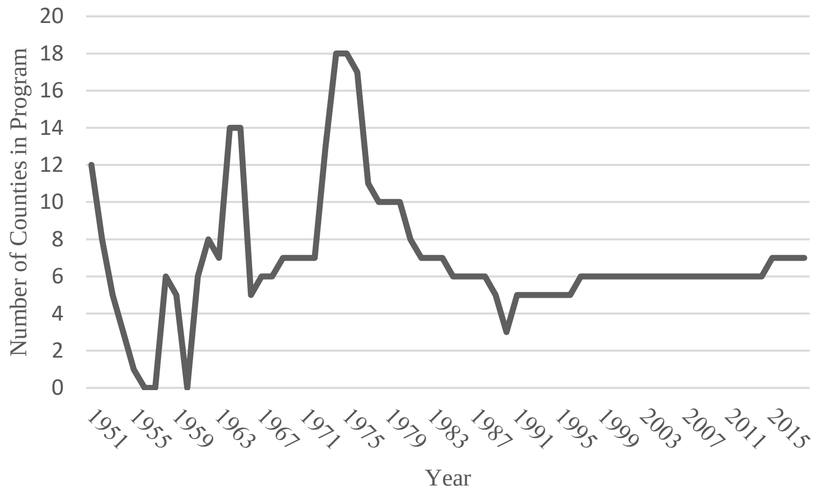

Figure 1 Number of counties participating in NDCMP (1951-2018)

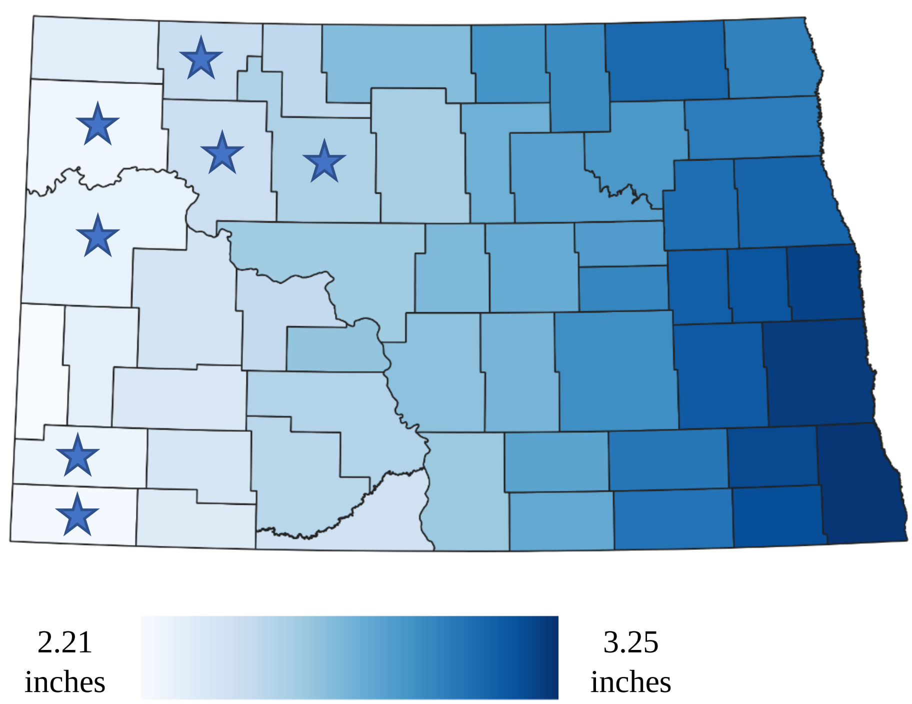

Figure 2 Average annual summer precipitation (in inches, June-August, 1951-2018), participating counties marked with stars

Some have questioned the validity of cloud seeding programs like the one in North Dakota. While there were several studies on cloud seeding in the 1970s and 1980s, none offer a definitive assessment of effectiveness. Previous studies that assessed the impacts of cloud seeding on crop yields that did not control for county fixed effects and county-specific time trends will be discussed later. I am unaware of any prior research investigating the effect of the cloud seeding program on loss ratios – defined as total indemnities paid to farmers divided by total premiums paid by farmers in a county in a given year – reported by the United States Department of Agriculture (USDA) Risk Management Agency (RMA).

More recently, economists have estimated that by saving crops from hail damage, the program generates approximately $6.9 million of value annually from 2008 to 2017 (Bangsund & Hodur, 2019). However, that study relied heavily on assumptions about the effectiveness of cloud seeding; most based a cloud seeding hail reduction factor of forty-five percent estimated by Smith (1997). Robust analysis of the program should not rely on assumptions about the percentage of crop losses saved by cloud seeding, and instead examine the impacts directly from crop yield data.

Water crises and extreme weather events continue to wreak havoc across the globe, and climate change research is unveiling more obstacles ahead. Now is an advantageous time to consider evaluating cloud seeding as a tool to combat risks to our food and water supply.

1.2 Cloud Seeding

In 1948, when Vincent Schaefer and Bernard Vonnegut submitted their patent for forming ice crystals in an air mass supersaturated with ice, the foundation for cloud seeding was created. Thereafter, interest in cloud seeding applications became widespread across the United States – and today all over the globe.

Currently, cloud seeding in North Dakota is conducted via airborne release of silver iodide (or dry ice) into a convective cloud marked as potentially hail-producing (hygroscopic seeding), or by direct injection from the top of a cloud. The goal of the seeding is to transform supercooled cloud droplets into ice crystals. In doing so, hailstone growth is stifled, thus rendering any falling hail less destructive after seeding and/or creating a greater amount of smaller hail. The program in North Dakota relies heavily on a contractor, Weather Modification International (WMI), which has conducted business in 19 countries and has clients ranging from private and public insurance agencies, to national and subnational government research organizations. Importantly, cloud seeding agents meet all National Environmental Policy Act requirements and are not deemed harmful to the environment in the dosages used (Weather Modification Association, 2009).

Any study of cloud seeding must be informed by an understanding of hailstorms themselves. Hailstorm studies were first conducted in Illinois using Weather Bureau records starting in the 1950s (Changnon, 1967). Those earlier studies provided the historical information on hail which would prove useful in later evaluating the efficacy of cloud seeding. The data published by Changnon (1962) proved useful for crop-hail insurance providers, so they determined it advantageous to fund further research about hail across the U.S. (Changnon & Stout, 1967). During this period, the Interdepartmental Committee of Atmospheric Sciences was given a recommendation to pursue a national program in weather modification. The recommendation stated that “[already] a number of government agencies have been developing plans for research and ultimately operational programs in weather and climate modification" (Newell, 1966).

With support from the National Science Foundation (NSF), researchers conducted one of the first thorough evaluation of the early hail suppression program in North Dakota. Citing the method developed by Schleusener and Jennings (1959), Butchbaker (1970) analyzed hailfall energy values, as well as the frequency of hailstorm occurrence, precipitation, and cloud radar reflectivity. He found, among other notable results, a thirty to sixty percent reduction in hail intensity in the target area compared with control areas, and significant differences in storm characteristics and seasonal hail energy between seeded and unseeded areas (Butchbaker, 1970). However, Miller et al. (1975) found no statistically significant difference in measurements of hail energy and hail depths between seed days and non-seed days.

Changnon (1977) published a status report of hail suppression across the globe (including projects in South Africa, Canada, Colorado, North Dakota, South Dakota, and Texas) in the Bulletin of the American Meteorological Society. He found reason hail suppression ranging from twenty to forty-eight percent, though most results were not statistically significant at the five percent level. Despite this initial evidence, opinion surveys of scientists offered a more pessimistic view of hail suppression, with many weather modification experts claiming no knowledge of a proven hail suppression capability.

Still, other researchers conducted numerous studies about the impact of cloud seeding on total mass of hail in a targeted area. Using data collected from a randomized seeding experiment conducted by the National Hail Research Experiment from 1972 to 1974, Crow et al. (1979) found no effect of seeding detected at even the ten percent significance level. Yet, they also explained that their research was based on a small sample size and emphasized the importance of obtaining larger samples in experimental areas to detect the underlying effect of seeding.

Since that time, more rigorous work has been undertaken with a focus on measuring reductions in hail damage as measured by changes in crop yields or crop insurance loss ratios. Further, research methods used to evaluate cloud seeding are improving. As technological instruments and three-dimensional data processing advancements are made, projects like SNOWIE (Seeded and Natural Orographic Wintertime Clouds: The Idaho Experiment) have leveraged such advancements to evaluate the potential of cloud seeding to bolster precipitation to enhance snowpack accumulation (Tessendorf, 2019).

1.3 Crop Yield and Crop Insurance

Pests, disease, and/or weather events can all damage crops, and are expected to decrease yields. Thus, if cloud seeding reduces damage caused by hail to crops in treated areas, one would expect crop yields to improve after treatment. Moreover, if seeding increases beneficial precipitation, one expects crop yields to improve when more precipitation is needed.

In his investigation, Hausle (1971) found favorable cost benefit ratios for cloud seeding. His method was as follows. First, he employed linear correlation, multiple regression, and ANOVA methods to analyze the effect of precipitation on native range grasses in Kansas. He then compared the economic benefits of improved forage yield based on a conservative one-half inch increase in precipitation with the annual economic costs of operating a cloud seeding program.

Swanson et al. (1972) used ordinary least squares (OLS) regression to estimate equations for Illinois corn and soybean yield response to changes in rainfall levels between 1931 and 1968. Then, by assuming hypothetical cloud seeding scenario outcomes (where seeding has a diminishing effect proportional to increases in the natural levels of precipitation), the researchers determined that cloud seeding could provide economic surplus much of the time over most of the state.

North Dakota small grain crops suffer greatly from hail damage during different stages of their development, and thus crop insurance is of paramount importance to farmers in the region (Wiersma & Ransom, 2005). Sonka & Potter (1977) estimated the possible benefits of hypothetical hail suppression effectiveness levels for wheat farmers in the Great Plains region (as wheat is particularly susceptible to hail damage), and then compared those benefits with other options available to farmers for reducing risks of hail damage to crops – such as hail insurance or all-risk insurance. The results indicated that, unless cloud seeding could decrease crop damage due to hail by twenty percent and increase rainfall by ten percent, prevailing insurance options would be more cost effective for farmers to adopt.

Following Miller & Fuhs (1987), Smith et al. (1997) compared Crop Hail Insurance Actuarial Association (CHIAA) loss ratios for western North Dakota cloud seeding target areas and eastern Montana adjacent control areas from 1924 to 1988. Results of the study suggested that crop hail insurance loss ratios in the NDCMP target area were forty-five percent lower than would be expected based on previous experience during the years 1976 to 1988. However, the changes in the loss ratios could not be directly linked to hail damage.

Economic analyses of cloud seeding program effectiveness have focused primarily on the monetary benefits tied to increased crop yields or lower costs associated with decreased risk of hail damage. Rose & Jameson (1986) analyzed loss-cost (insured losses divided by liabilities in a given county during a given year) data for target and control areas in North Dakota and Montana, weighted by the number of counties comprising an area. They created double mass plots of the weighted loss-costs and used the Mann-Whitney U test to check for distributional differences. The results of the study were insufficiently consistent to convince the researchers of the program's effectiveness. Later, Johnson et al. (1989) went further to assess the economic impacts of cloud seeding in North Dakota by calculating "crop output potentially savable" based on the CHIAA loss-cost ratios, gross crop production, and a 43.5 percent loss reduction factor (Smith et al., 1987). Under this program efficacy assumption, over the 1976 to 1985 study period, the researchers estimated a ten-year average annual savings of approximately $3.8 million based on the total value of crops saved from hail damage, for the six treated counties (Johnson et al., 1989).

Other researchers have evaluated the NDCMP's economic impact using updated crop production and insurance data. However, these reports have assumed the historically estimated forty-five percent reduction in loss ratios of the NDCMP target area may be interpreted as a forty-five percent reduction in actual crop hail damage and applied to estimations of changes in crop supply going forward (Bangsund & Hodur, 2019; Bangsund & Leistritz, 2009). While the reports do well at estimating monetary benefits of the program under certain conditions, the authors admit several coefficients are based on estimates from aging studies.

1.4 Research Objective

The literature about cloud seeding and its effectiveness as a damage-reducing agent is vast, but it offers few statistically significant results. Perhaps just as important, there has been an absence of peer-reviewed articles on the topic in recent decades.

According to the NDARB, cloud seeding treatment is considered most beneficial in terms of reducing hail damage done to small grain crops, which are very susceptible to damage

(Lemons, 1942). According to the NDSU handbook for farmers, wheat (spring and durum varieties), barley, and oats are the primary types of small grain crops in the state. It further recommends that those crops be planted between the second week of April and first week of May (depending on location) to optimize yield potential (Wiersma & Ransom, 2005). Typically, those same crops are harvested throughout the month of August (USDA National Agricultural Statistics Service, 2010).

The present study examines the impact of program participation in North Dakota on wheat and barley yields and associated changes to crop insurance metrics. For the remainder of the paper, if a county participated in the program in any given year it will be considered part of the "seeded" group (where "seeded" is synonymous with "participated in the program" or "treated") for that year. In other words, cloud seeding is measured by a binary variable equal to one if a county participated in the NDCMP program for a given year, and zero if it did not in that year. Unfortunately, individual cloud seeding treatment event data for each county and year are not available. Given the data constraints, participation in the program at the county level for a given year is the best approach available for measuring the potential effect of cloud seeding.

Not only does the current study address the impact of cloud seeding on loss ratios, it also estimates the impacts on indemnity payouts (contractual payments made to insured parties when yield losses have been incurred above and beyond a yield guarantee). Oats and winter wheat are not included in the analyses because of the relatively small number of acres planted and harvested in western North Dakota. Moreover, winter wheat is planted in one year and harvested in the next; making it difficult to isolate the contemporaneous effect of program participation.

This study focuses on the thirty-year period between 1989 and 2018 in order to leverage available RMA data for crop insurance outcomes in the state. Over the thirty-year period, it is important to note that six changes in county program participation occurred – meaning that a county either dropped out or entered into the program a total of six times – because the fixed effects estimation approach relies on changes in treatment status to form the parameter estimate. Figure 3 shows the number of years each county in North Dakota received treatment during the period. The counties which received treatment at least once during the period are: Bowman, Burke, McKenzie, Mountrail, Slope, Ward, and Williams.

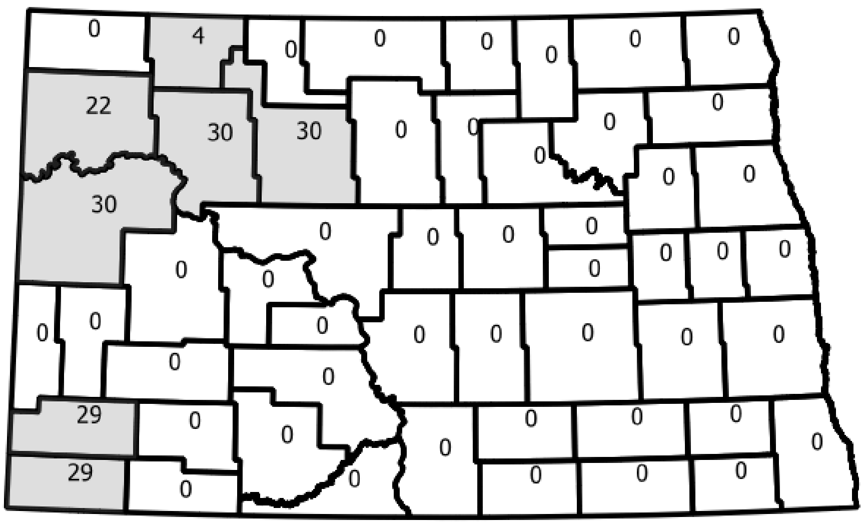

Figure 3 Number of years a county participated in NDCMP (1989 – 2018)

The primary analyses of cloud seeding treatment impacts are conducted with a balanced county panel using the fixed effects regression estimation method accounting for county and time effects as well as county-specific time trends. Time effects are important to control for in any crop yield analysis because of the general improvement in farming practices and crop varieties over time. Figure 4 highlights the counties included in the primary sample (a full list of all included counties is provided in Appendix A). Despite the use of fixed effects, it should be noted that counties self-select into the program, and thus there is potential self-selection bias.

Bordering counties in Montana and South Dakota are included in the primary sample because of their proximity to the treated North Dakota counties, and because of their similarity in weather patterns. Previous research has used counties in eastern Montana as a control group for analysis for similar reasons (Miller & Fuhs, 1987; Smith et al., 1997).

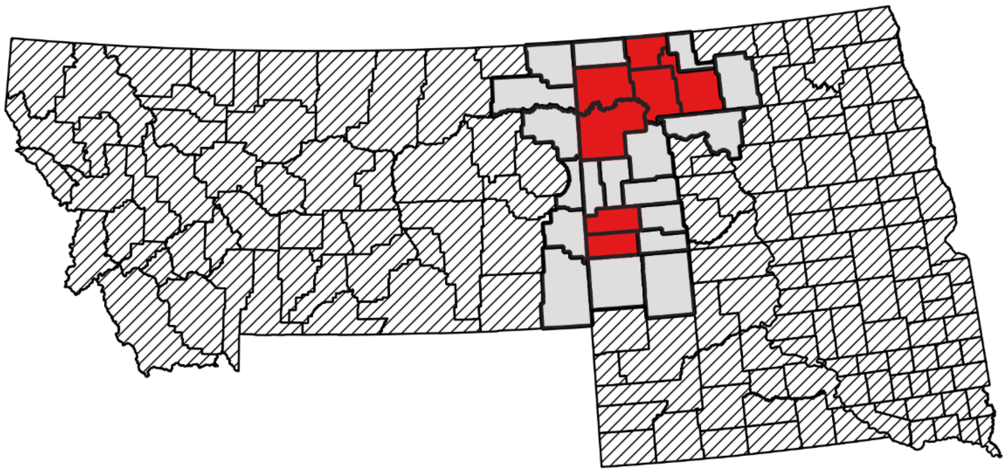

Figure 4 Montana, North Dakota, and South Dakota counties included in the primary sample (treated counties highlighted in red, non-treated highlighted gray)

It is best to compare counties with similar climatological patterns when evaluating the effect of a program which intends to alter extreme weather events. Thus, North Dakota counties neighboring the treated counties are included along with the Montana and South Dakota counties in the primary sample.

This is the first study of the NDCMP's effectiveness at improving crop yields to apply such an econometric model specification, and it is the first to fully conceptualize the role of cloud seeding as a damage control agent in a crop yield model. I also offer an evaluation of robustness using a secondary sample including all the counties in North Dakota, differing time periods, and a stepwise omission of each treated counties. I also use the estimates generated from the primary analysis to compare and assess the validity of previous studies.

The remainder of this study is organized as follows. First, the conceptual framework is presented. Then, the data and empirical approaches are explained. Third, results of the empirical analyses are discussed. The final chapter concludes with a discussion of cloud seeding effectiveness, limitations in the research, and opportunities for further study.

CHAPTER 2: CONCEPTUAL FRAMEWORK

As cloud seeding is conducted in an effort to reduce hail damage, counties which receive cloud seeding should experience fewer crop losses than those that do not, all else equal. With fewer crop losses, participating counties should have fewer hail-related insurance claims and lower payments for damages. Following the damage control function approach established by Lichtenberg and Zilberman (1985), cloud seeding treatment enters a small grain crop yield damage abatement function as a damage control agent (equation 1).

$$Y_{ikt}(\boldsymbol{Z}, X) = Y_{ikt}^{0}(\boldsymbol{Z}) + Y_{ikt}^{1}(\boldsymbol{Z})G_{kt}(X) \tag{1}$$

Where $Y_{ikt}^{0}(\boldsymbol{Z})$ is the minimum output for crop i in county k at time t given some vector of inputs $\boldsymbol{Z}$, and $Y_{ikt}^{0}(\boldsymbol{Z}) + Y_{ikt}^{1}(\boldsymbol{Z})$ represents the potential output. $G_{kt}(X)$ is the damage abatement function, where $G_{kt}(X) = 1$ represents the achievement of maximum abatement. $G_{kt}(X)$ is written as:

$$G_{kt}(X) = 1 - \{D_{kt}[H(1 - X)]\} \tag{2}$$

Where $G_{kt}(X) \in [0,1]$ represents the proportion of damage abated, and X represents the efficacy of program participation. As $X \to 1,\ G_{kt}(X) \to 1$. This is because $D_{kt}[H(1 - X)] \in [0,1]$ represents the damage from hail occurring in a county during a given period, and

$D_{kt}[H(1 - X)] \to 0$, as $X \to 1$. This study tests the hypothesis that cloud seeding will increase crop yield by reducing hail damage as illustrated by equation 2.

The general linear form shown in equation 2 implies additive separability of potential output and losses. Although it is possible that output could be nonlinear in abatement, it does not seem likely in the case of cloud seeding. In contrast to pest management, where marginal productivity of abatement declines as pest populations decrease, the effect of county participation in the program is not expected to diminish over time. Though the seeding of individual storms in any given year could potentially have a diminishing effect on crop yields, the present analysis does not analyze individual storm data.

If X plays a significant role in abating damages, it should also play some role in crop insurance premium rates, indemnity payments, and loss ratios. Following Goodwin (1994), the Federal Crop Insurance Corporation (FCIC) calculates premium per acre (PPA) as a function of specific attributes including: price guarantee, yield guarantee, yield estimate, premium rate, and subsidy amount. Premium rates are determined at the county-level through an elaborate process (Goodwin, 1994). To simplify, the total premium for each county is written as:

$$P_{ikt} = F[Y_{ikt-1}(\boldsymbol{Z}, X), L_{ikt-1}(X), \boldsymbol{\delta}] \qquad (3)$$

Where P_{ikt} is the total premium estimated for crop i in county k at time t, $Y_{ikt-1}(\boldsymbol{Z}, X)$ is the crop yield from time period $t-1$, $L(X)$ represents the loss ratio history, and $\boldsymbol{\delta}$ is a vector of additional scalars used as smoothing factors. To better understand how X enters the model, the partial derivative is taken (equation 4).

$$\frac{\partial P_{ikt}}{\partial X} = \frac{\partial F}{\partial Y_{ikt-1}} \frac{\partial Y_{ikt-1}}{\partial X} + \frac{\partial F}{\partial L_{ikt-1}} \frac{\partial L_{ikt-1}}{\partial X} \qquad (4)$$

By decomposing the above, one can see that an increase in X is expected to have a negative impact on total premiums. It follows from Goodwin (1994) that $\frac{\partial F}{\partial Y_{ikt-1}} < 0$ (counties with higher average yields realize premium rate discounts), and $\frac{\partial Y_{ikt-1}}{\partial X} > 0$ by expectation of the relationship between cloud seeding and yield. Thus, the left term on the RHS is decidedly negative. Moreover, $\frac{\partial F}{\partial L_{ikt-1}} > 0$ as riskier counties are charged higher premiums, and $\frac{\partial L_{ikt-1}}{\partial X} < 0$

by the expectation that cloud seeding acts as a damage control agent, and with a greater efficacy will in turn reduce losses over time.

Indemnity payments are only made when realized yields are less than the agreed upon yield guarantee. Indemnities cannot be equated directly to total losses because a deductible threshold must be met before any indemnity payout is made. An indemnity payment for a given crop, county, and time period is equal to the yield guarantee less than the actual yield multiplied by the insured price. However, normalizing the price to one, the indemnity payment can be written as a function of actual yield (equation 5):

$$I_{ikt} = F[Y_{ikt}(\boldsymbol{Z}, X)] \tag{5}$$

If the actual yield is less than the guaranteed yield, one can interpret a change in X taking the partial derivative (equation 6).

$$\frac{\partial I_{ikt}}{\partial X} = \frac{\partial F}{\partial Y_{ikt}} \frac{\partial Y_{ikt}}{\partial X} \tag{6}$$

Stated earlier, it is expected that $\frac{\partial Y_{ikt}}{\partial X} > 0$ holds up to a maximum crop yield point. $\frac{\partial F}{\partial Y_{ikt}} < 0$ should also hold because as actual yield increases, the amount of indemnities being paid decreases toward zero. Thus, cloud seeding ought to have a negative impact on indemnity payments.

What has effectively been shown is a decomposition of the loss ratio. The loss ratio is a measure defined as indemnities paid divided by premiums (equation 7).

$$L_{ikt} = \frac{I_{ikt}}{P_{ikt}} \tag{7}$$

Taking the partial derivative of equation 7 with respect to X yields:

$$\frac{\partial L_{ikt}}{\partial X} = \frac{\partial F}{\partial I_{ikt}}\frac{\partial I_{ikt}}{\partial X} + \frac{\partial F}{\partial P_{ikt}}\frac{\partial P_{ikt}}{\partial X} \tag{8}$$

There is one particularly interesting result. If $\frac{\partial F}{\partial I_{ikt}}\frac{\partial I_{ikt}}{\partial X} < 0$ and $\frac{\partial F}{\partial P_{ikt}}\frac{\partial P_{ikt}}{\partial X} > 0$ the effect of a change in X on L_{ikt} is determined by the magnitude of the two partial effects on the RHS. For instance, if crop damage abatement reduces indemnity payments made by FCIC more than it reduces premiums charged by FCIC, then loss ratios will decline because of greater efficacy of cloud seeding. However, if the FCIC reduces premiums more significantly due to cloud seeding and the effect is stronger than the effect of X on indemnity payments, then the loss ratios may increase over time. If indemnities decrease more than premiums year over year, then insurance companies benefit from cloud seeding. If premiums decrease more than indemnities year over year, then farmers might benefit more than insurance companies from cloud seeding. In effect, if $\frac{\partial L_{ikt}}{\partial X}$ is less than zero it is because cloud seeding impacts indemnities more than premiums in the current period.

Therefore this study also tests the hypotheses that (i) insurance indemnities will decline as a result of cloud seeding (illustrated by equation 6), and (ii) that loss ratios will fall due to cloud seeding reducing crop damage (illustrated by equation 8). Loss ratios are predicted to fall as a result of cloud seeding because indemnities are expected to decline faster than premiums. The impact of cloud seeding on premiums is not investigated here due to the complex nature of premium setting calculations.

CHAPTER 3: EMPIRICAL ANALYSIS

3.1 Data Sources

The North Dakota Atmospheric Resource Board (NDARB) provided the NDCMP historical cloud seeding data, which is critical for my analysis. Without such panel data, it would not be possible to conduct the evaluation using the fixed effects approach. The data includes information about which counties participated in the NDCMP program from 1951 to 2018, and whether or not a county participated in a given year. I use a thirty-year subset of the NDCMP data for this study. As was noted earlier, border counties in Montana and South Dakota are included in the primary sample as part of the control group because of their proximity to the treated counties and their similarity in climatological patterns. In Table 1, I present a comparison of precipitation and temperature data between the treated counties in North Dakota and those bordering in Montana and South Dakota. The table also offers a comparison of the western counties in North Dakota with those in the eastern side of the state (not included in the primary sample). The average temperatures across the subsamples do not vary greatly, but the precipitation in eastern North Dakota is roughly half an inch greater than the western part.

Table 1 Average precipitation and temperature data from May to August across different groups of counties from 1989 to 2018

	Bordering Counties	**Treated Counties**	**Western North Dakota**	**Eastern North Dakota**
Average Precipitation (May to August, inches)	2.27	2.43	2.48	3.00
Average Temperature (May to August, °F)	63.8	63.2	63.2	63.7

Wheat and barley yield panel data were obtained from the data from the USDA National Agricultural Statistics Service (NASS).[1] NASS collects information through sample surveys and only reports annual information on yields. Note that the surveys do not necessarily cover all of the farmers harvesting a crop in a given year. For that reason, crop data presented and used herein is incomplete in nature. Spring and durum wheat acres planted and harvested are aggregated, with their yields averaged to capture the total effect of the program. The data were combined because both types of wheat are harvested in the late summer and crop insurance outcomes are not specified for the individual types of wheat, but for wheat in general. Table 2 provides summary statistics for those crops. Seeded counties have higher thirty-year average wheat and barley yields than non-seeded counties, suggesting the potential for cloud seeding impacts.

Table 2 Small grain crop descriptive statistics: seeded and non-seeded counties in primary sample (1989-2018)

Variable	Seeded – mean (sd)	Non-seeded – mean (sd)
Wheat[a]		
Planted (acres)	238,673 (129,966)	166,596 (114,423)
Harvested (acres)	230,334 (127,771)	159,436 (112,393)
Yield (bu/harvested acre)	31.2 (8.06)	28.3 (8.01)
N	166	528
Barley		
Planted (acres)	31,013 (24,120)	21,160 (19,679)
Harvested (acres)	27,839 (24,292)	18,594 (19,807)
Yield (bu/harvested acre)	48.80 (12.5)	42.75 (12.8)
N	147	450

Note[a] - Wheat acres planted, acres harvested, and yield are generated with spring and durum wheat data

Crop insurance panel data starting in 1989 was obtained from the RMA, and includes such information as total indemnities, total premiums and loss ratios associated with crops

[1] Detailed data are available at https://quickstats.nass.usda.gov/

normally harvested in any given year. [2] As of 2019, the RMA insured eighty percent of planted barley acres and ninety-nine percent of planted wheat acres across North Dakota (USDA Risk Management Agency, 2019). All crop insurance products provided by insurers working through the RMA are included in the model because they mention some policy component potentially linked to receiving protection from yield loss. Although the multiple peril crop insurance provided by the FCIC covers hail damage, most crop-hail policies are provided directly to farmers by private insurers outside of the federal crop insurance program, so the RMA data used in this study only represents a subset of the relevant crop-hail insurance information. Table 3 provides summary statistics of the RMA Summary of Business (SOB) data for seeded and non-seeded counties over the period. Seeded counties appear to receive more indemnity payouts per insured acre and pay higher premiums than non-seeded ones over the thirty-year period, on average. Non-seeded counties have significantly higher average loss ratios than seeded ones over the period, however.

Table 3 Small grain crop insurance descriptive statistics: seeded and non-seeded counties in primary sample (1989-2018)

Variable	Seeded – mean (sd)	Non-seeded – mean (sd)
Wheat		
Indemnity per insured acre ($)	14.6 (24.0)	13.2 (22.5)
Premium per insured acre ($)	16.9 (12.6)	14.4 (11.8)
Loss ratio	0.801 (0.898)	0.908 (1.01)
N	174	576
Barley		
Indemnity per insured acre ($)	11.7 (18.6)	11.3 (19.6)
Premium per insured acre ($)	13.5 (10.3)	11.5 (9.68)
Loss ratio	0.827 (0.935)	0.947 (1.04)
N	174	575

Note - *N* (sample size) in Table 3 is greater than in Table 2 because NASS data is not as complete (and winter wheat is not included in Table 2)

[2] Detailed data are available at https://www.rma.usda.gov/Information-Tools/Summary-of-Business/State-County-Crop-Summary-of-Business

Since the RMA crop insurance data is only available beginning in 1989, a subset of the NDCMP county participation data from 1989 to 2018 is used for the analysis.

Precipitation and temperature are considered part of the vector of inputs affecting crop yields defined in equation 1. To control for variation in moisture and temperature stress levels, growing degree days (GDD), stress degree days (SDD), and Palmer Z (PZ) index variables are generated using data from NOAA. These weather variables are chosen rather than the traditional average precipitation and temperature variables because of the nature of crop yield response to extreme moisture and temperature conditions (Schlenker & Roberts, 2009). Additionally, cloud seeding activity does not take place when precipitation levels are too low; so, I control for changes in drought severity (using the PZ) instead of changes in average precipitation. GDD represents the sum over growing season days between upper and lower temperature thresholds (0°C and 29°C, respectively), whereas SDD represents the sum over growing season days above an upper threshold (30°C) where the photosynthesis process begins to diminish thus hindering small grain crop development.[3]

GDD and SDD are calculated using station-level daily maximum and minimum temperatures provided by NOAA's Global Historical Climatology Network (GHCN) data set.[4] The station-level data are transformed into county-level data by taking average daily temperatures for all stations within a given county from May to August (coinciding with the growth period of the crops). County-level PZ values are obtained by transforming NOAA climate division-level data.[5] Following an established procedure, area intersections between

[3] More detail on the formulation of GDD and SDD is provided in Che et al. (2019)
[4] Detailed data are available at ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/daily/by_year/
[5] Detailed data are available at https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/

climate divisions and counties are calculated, and then PZ values are weighted by county intersection areas (Che et al., 2019). PZ values may be interpreted as follows: PZ ≤ -2 indicates drought; PZ ≥ 5 indicates flood conditions; and PZ = 0 represents neutral moisture conditions (Xu et al., 2013).

Consistent with Che et al. (2019), I evaluate dry and wet weather conditions separately by using PZ to generate

$$Dry_{it} = -\min\ (0, PZ_{it}) \tag{9}$$

$$Wet_{it} = \max\ (0, PZ_{it}) \tag{10}$$

where PZ_{it} is the May to August average PZ value for county *i* during year *t*. With Dry_{it} and Wet_{it} defined by equations 9 and 10, one can interpret increases in either variable with associated increases in dryness or wetness, respectively.

Limitations in the available hail frequency and magnitude data make it impossible to reliably estimate the program's direct effect on hail over the thirty-year period being studied. The NOAA storm events database provides a general record of hail events in the United States, but because the events are mainly reported by an observer network, the record is partial and cannot be fully trusted. Although NOAA keeps accurate records of precipitation, a study of the cloud seeding treatment effect on precipitation levels is outside the scope of this study. Recall that increasing beneficial precipitation is a secondary goal of the NDCMP program.

3.2 Small Grain Crop Yield Model

To investigate the impact of the NDCMP program on crop yields, I use a two-way fixed effects regression framework because I have panel data and want to control for unobserved, time-invariant factors at the county-level that may bias the program participation decision (e.g., political majority, religious majority, etc.). I conduct Hausman Tests, Breusch-Pagan Lagrange Multiplier Tests, and an alternative panel overidentification test where the random effects and pooled OLS estimation methods are rejected. The explanatory variable of interest is the binary variable indicating whether a county was seeded in any given year. As noted earlier, counties which participated were not randomly assigned. Also, the NDCMP operates on a state cost-share basis where a county chooses to participate in any given year. The potential bias introduced by nonrandom county participation is a concern and thus caution is warranted in our interpretation of the coefficient estimates. I will discuss this point more later. Formally, the reduced form model is written as follows:

$$Y_{ikt} = \alpha Seeding_{kt} + \beta Dry_{kt} + \delta Wet_{kt} + GDD_{kt} + SDD_{kt} + t_t + c_k + t_t * c_k + \epsilon_{ikt} \tag{11}$$

Where the dependent variable is the annual yield (calculated by total production in bushels divided by total harvested acres) of crop i in county k at year t. $Seeding_{kt}$ is a binary variable taking on the value one when a county received cloud seeding treatment in year t. Dry_{kt} and Wet_{kt} represent how dry or wet weather conditions were from May to August for a given county k at year t. GDD_{kt} and SDD_{kt} represent growing degree days and stress degree days, respectively. t_t represents a vector of time indicator variables, c_k controls for county fixed effects, $t_t * c_{tk}$ represents county specific time trends, and ϵ_{ikt} is the error term.

Table 4 presents definitions and hypothesized effects of the variables that appear in the crop yield models. Recall from the conceptual framework that $Seeding$ is expected to have a positive effect on crop yields across small grain crops. Higher than usual temperatures in the middle of summer are expected to have a negative impact on wheat and barley yields (Klink, et al., 2013; Lanning et al., 2010; Wiersma, 2018) Thus, one expects an increase in SDD to be correlated with a decrease in yields and GDD with an increase in yields. Increased moisture levels could have a positive or negative effect depending on the timing of rainfall changes; increases earlier in the season may increase yields, while additional rainfall later in the season may result in waterlogging and decrease yields (Hakala et al., 2012; Setter & Waters, 2003). Meanwhile, as plants require sufficient moisture to properly develop, I expect dry weather conditions will negatively impact yields.

Table 4 Summary of variables: primary sample crop yield models

Variable	Variable Definition (units)	Mean (sd)	Expected Effect
Dependent			
Wheat yield	Bushels per harvested acre	29.0 (8.12)	
Barley yield	Bushels per harvested acre	44.2 (13.0)	
Variable of Interest			
Seeding	County participated in NDCMP program	0.232 (0.422)	+
Other Explanatory			
Dry	Negative minimum among 0 and the PZ value	0.696 (0.939)	-
Wet	Maximum among 0 and the PZ value	1.07 (1.58)	+/-
GDD	May-August growing degree days	2,104 (147)	+
SDD	May-August stress degree days	42.2 (37.9)	-

3.3 Crop Insurance Model

As with the crop yield model, a nearly identical fixed effects regression framework is used to estimate the impact of cloud seeding on crop insurance indemnities and loss ratios.

The reduced form models for indemnities per insured acre and loss ratios are written as follows:

$$I_{ijkt} = \alpha Seeding_{kt} + \beta Dry_{kt} + \delta Wet_{kt} + GDD_{kt} + SDD_{kt} \qquad (12)$$

$$+ t_t + c_k + t_t * c_k + \epsilon_{ikt}$$

Equation 12 follows the same variable labeling convention as equation 11 with an important exception. The dependent variable I_{ijkt} specifies the insurance outcome of interest, indicated by the subscript j, being explained in each model. Those outcomes are county-level indemnities per insured acre paid to farmers, and the county-level loss ratio calculated as total indemnities over total premiums in the same period. The models are estimated with robust standard errors.

Table 5 presents definitions and hypothesized effects of the variables that appear in the crop insurance models. Based on the conceptual framework, $Seeding$ is expected to have a negative effect on indemnities driven by the reduction in insurance claims made in the treated counties. Based on the conceptual framework, cloud seeding should have an overall negative effect on loss ratios because indemnities are expected to decrease faster than premiums. I expect increases in GDD, SDD, and Dry will have effects of opposite sign to those presented in Table 4, with Wet having an indeterminant effect.

Table 5 Summary of variables: primary sample crop insurance models

Variable	Variable Definition (units)	Mean (sd)	Expected Effect
Dependent			
Wheat indemnity per insured acre	Indemnities paid over insured acres	13.5 (22.9)	
Barley indemnity per insured acre	Indemnities paid over insured acres	11.4 (19.3)	
Wheat loss ratio	Ratio of total indemnities to total premiums paid	0.883 (0.989)	
Barley loss ratio	Ratio of total indemnities to total premiums paid	0.919 (1.02)	
Variable of Interest			
Seeding	County participated in NDCMP program	0.232 (0.422)	-
Other Explanatory			

Table 5 (cont'd)

Dry	Negative minimum among 0 and the PZ value	0.696 (0.939)	+
Wet	Maximum among 0 and the PZ value	1.07 (1.58)	+/-
GDD	May-August growing degree days	2,104 (147)	-
SDD	May-August stress degree days	42.2 (37.9)	+

3.4 Robustness Checks

Aside from deriving estimates from the primary sample detailed thus far, a secondary sample composed of all fifty-three counties in North Dakota is used to investigate the effect of program participation in a single jurisdiction. While the primary sample was created based on proximity and climatological attributes, the secondary sample allows for the comparison of treated and control counties presumably experiencing similar state-level effects. Given that counties put participation in the program to a vote, I expect that the model estimates from the secondary sample are likely biased upward (estimates are presented in the Robustness Estimation section of Chapter 4). Counties that choose to join the program are those that must expect to gain the greatest benefit, and so any apparent gains correlated with program participation might be larger for those counties when compared with others in the state.

With only seven counties participating in the program from 1989 to 2018, it is likely that some counties could be more responsible for results obtained than others. To investigate this possibility, another robustness check is conducted to evaluate how model estimates changed when specific counties were individually dropped from the sample. Thus, I estimate a set of regressions seven times (one for each dropped county) with augmented samples (see Appendix B for estimation results).

Finally, because of the lack of variation in program participation from 1989 to 2018, a time sensitivity analysis is made. $Seeding$ coefficient estimates from the wheat yield model are obtained using the same specification as before, but over differing time periods. Starting with the period from 1949 to 2018, robustness of the $Seeding$ coefficient estimate is checked in ten-year increments stopping with the original period starting in 1989. Then, the same procedure is followed starting with the period from 1949 to 2014. With this approach, I offer wide range of fixed effects estimates based on alternative timeframes to increase confidence in the overall evaluation. Furthermore, this component of the analysis may offer insight on possible changes in program effectiveness over time (see Appendix B for estimation results).

CHAPTER 4: RESULTS

4.1 Small Grain Crop Yield Estimation

Table 6 Cloud seeding effect on wheat and barley yields in the primary sample (1989-2018), fixed effect regressions

	Wheat Yield	Barley Yield
Seeding	3.87**	4.20
	(1.59)	(4.98)
Dry	-3.12***	-5.38***
	(0.329)	(0.553)
Wet	0.534*	-0.950*
	(0.296)	(0.533)
GDD	-0.00175	-0.00739
	(0.00202)	(0.00636)
SDD	-0.00940**	-0.0159***
	(0.00422)	(0.00383)
Observations	688	597
R-squared	0.731	0.749

*** p<0.01, ** p<0.05, * p<0.1

Table 6 presents the results for the small grain crop yield models where wheat and barley yields are regressed on the weather variables and cloud seeding. As a reminder, all models are estimated with yearly fixed effects, county fixed effects, and county-specific time trends. As hypothesized, the relationship between the cloud seeding treatment and small grain crop yield is positive for both of the crops. However, the effect of cloud seeding on barley is not statistically significant in this model specification.

These results show that counties participating in the NDCMP program grow 3.87 bushels more of wheat per harvested acre than counties not participating, on average. For perspective, in the thirty-year period, the average wheat yield was approximately 28.98 bushels per harvested acre. In other words, participating counties' wheat yields are about thirteen percent higher than non-participating counties, on average.

The coefficient on Dry is negative, as well as practically and statistically significant for both crops. As expected, Wet has both positive and negative estimated coefficients for wheat and barley, respectively. Though both estimated coefficients are statistically significant, they are of much lesser magnitude than those related to drought conditions. While GDD is not statistically significant in estimating crop yields on the margin, SDD is negative and statistically significant.

4.2 Crop Insurance Estimation

Table 7 Cloud seeding effect on loss ratios for wheat and barley in the primary sample (1989-2018), fixed effect regressions

	Wheat Loss Ratio	Barley Loss Ratio
Seeding	-0.548*	-0.231
	(0.316)	(0.295)
Dry	0.654***	0.576***
	(0.0451)	(0.0420)
Wet	0.0968**	0.0917**
	(0.0377)	(0.0428)
GDD	0.000422	0.000562
	(0.000450)	(0.000420)
SDD	0.00191	0.00187
	(0.00168)	(0.00149)
Observations	743	742
R-squared	0.529	0.578

*** p<0.01, ** p<0.05, * p<0.1

Table 7 contains results for the crop insurance loss ratio models. The relationship between the cloud seeding treatment and small grain crop insurance loss ratios is significant and negative for wheat at the ten percent significance level. Thus, counties participating in the NDCMP have loss ratios related to wheat about 0.548 lower than counties that do not, on average. Thus, it seems that cloud seeding affects wheat indemnities more than premiums in the short term. Moreover, the results suggest that insurers and the FCIC accrue a benefit from the cloud seeding treatment. These results also suggest that moisture conditions have a statistically significant effect on loss ratios. A one-unit increase in Dry is associated with a 0.654 increase in loss ratios for wheat and a 0.576 increase for barley, on average.

Table 8 Cloud seeding effect on indemnities per insured acre for wheat and barley in the primary sample (1989-2018), fixed effect regressions

	Wheat Indemnity	Barley Indemnity
Seeding	-9.55	-9.02
	(7.86)	(7.56)
Dry	7.60***	4.58***
	(1.00)	(0.625)
Wet	0.0599	-0.805
	(0.888)	(0.657)
GDD	0.0244**	0.0132
	(0.0112)	(0.00850)
SDD	0.0365	0.0292
	(0.0266)	(0.0196)
Observations	743	742
R-squared	0.619	0.692

*** p<0.01, ** p<0.05, * p<0.1

Table 8 presents results for the crop insurance indemnity models regressed on the same covariates as those in the loss ratio models. The cloud seeding treatment has a negative estimated effect on indemnity payments for wheat and barley. However, neither estimated coefficient is statistically significant. Although, when estimating the same equations with total indemnities as the dependent variable, the effect of cloud seeding is statistically significant.

An increase in drought conditions from May to August is estimated to have a significant and positive impact on indemnity payments for wheat and barley. The practically insignificant estimated coefficients associated with changes in GDD or SDD are indicative of the fact that indemnity payouts are usually linked with weather phenomenon that are stochastic and devastating in nature (like hail). However, the statistically significant coefficient on GDD seems contradictory to expectation. The unexpected coefficient estimate of GDD could be the result of increases in the number of growing degree days (when temperature is within an ideal growing range) being correlated with hail and other devastating weather events. Hail forms when moisture is carried in updrafts, but if temperatures are too high (or precipitation too low) this type of phenomenon may not occur.

Overall, the results of the wheat insurance model estimations lend some support to the hypothesis that cloud seeding treatment is correlated with reduced insurance loss ratios and indemnities paid by insurers working with the FCIC by way of reducing crop damages in treated counties. However, the results for barley are statistically insignificant.

4.3 Robustness Estimation

To examine the robustness of the small grain crop yield and crop insurance regression estimates, I estimate several different model specifications and methods.

First, a secondary sample is constructed including all of the counties in North Dakota. Since the program is accessible to any county in the state, and the climatological patterns across the state vary greatly, this secondary sample differs much from the primary sample and seems fitting to test robustness of the results presented thus far for reasons mentioned in Chapter 3. Table 9 presents summary statistics for wheat and barley across the counties in the secondary sample. Unlike with the primary sample, non-seeded counties have higher thirty-year average wheat and barley yields than seeded ones in the secondary sample. This difference in means supports the notion that there is a self-selection bias problem in the data whereby counties with lower average yields opt into the NDCMP program because they suffer more significantly from hail damage.

Table 9 Small grain crop descriptive statistics (secondary sample): seeded and non-seeded counties (1989-2018)

Variable	Seeded – mean (sd)	Non-seeded – mean (sd)
Wheat		
Planted (acres)	238,673 (129,966)	164,274 (98,291)
Harvested (acres)	230,334 (127,771)	158,249 (95,893)
Yield (bu/harvested acre)	31.2 (8.06)	35.1 (11.7)
N	166	1,312
Barley		
Planted (acres)	31,013 (24,120)	35,001 (34,076)
Harvested (acres)	27,839 (24,292)	32,930 (33,065)
Yield (bu/harvested acre)	48.8 (12.5)	52.9 (13.7)
N	147	1,179

Secondary sample fixed effect regression estimation results for the small grain crop yield models are given in Table 10. The estimation results largely corroborate the primary sample results. The relationship between cloud seeding and small grain crop yield is positive and statistically significant for wheat (as with earlier, but now at the less than one percent level and of greater practical magnitude), and positive for barley. The results imply that cloud-seeded counties gain 6.19 bushels of wheat per harvested acre more than non-seeded counties, all else held equal. The estimated coefficients for the weather control variables (Dry, Wet, GDD, and SDD) are all of stronger practical significance. Interestingly, the estimated coefficient on Wet is negative for both crops, and statistically significant at the less than one percent level. Whereas, in the primary sample, the coefficient on Wet was positive for wheat. The reason for the change in sign is likely because the primary sample receives less rainfall, on average, than the secondary sample (see Table 1).

Table 10 Cloud seeding effect on wheat and barley yields in the secondary sample (1989-2018), fixed effect regressions

	Wheat Yield	Barley Yield
Seeding	6.19***	6.29
	(2.05)	(4.33)
Dry	-4.99***	-5.76***
	(0.471)	(0.662)
Wet	-0.784***	-1.77***
	(0.224)	(0.321)
GDD	0.00184*	0.000490
	(0.00104)	(0.00177)
SDD	-0.0833***	-0.105***
	(0.0185)	(0.0206)
Observations	1,397	1,261
R-squared	0.742	0.716

*** p<0.01, ** p<0.05, * p<0.1

Table 11 presents summary statistics for loss ratios, indemnities, and premiums across the counties in the secondary sample. As with the primary sample, thirty-year average loss ratios for wheat and barley are a good deal higher in the non-seeded counties. However, unlike the primary sample, thirty-year average indemnities and premiums per insured acre related to barley and premiums per insured acre related to wheat are lower in seeded counties than in non-seeded counties. In part, this could be because higher historical loss ratios in non-seeded counties drive premium prices more than average yield does. Average barley losses could be worse in non-seeded counties because of differences in precipitation across the state (especially the eastern part, which receives more rainfall on average). Wheat indemnities per insured acre are still slightly larger for seeded counties than non-seeded ones.

Table 11 Small grain crop insurance descriptive statistics (secondary sample): seeded and non-seeded counties (1989-2018)

Variable	**Seeded – mean (sd)**	**Non-seeded – mean (sd)**
Wheat		
Indemnity per insured acre ($)	14.6 (24.0)	13.4 (20.7)
Premium per insured acre ($)	16.9 (12.6)	17.9 (14.7)
Loss ratio	0.801 (0.898)	0.903 (1.10)
N	174	1,416
Barley		
Indemnity per insured acre ($)	11.7 (18.6)	13.3 (20.9)
Premium per insured acre ($)	13.5 (10.3)	14.8 (12.4)
Loss ratio	0.827 (0.935)	1.02 (1.12)
N	174	1,413

Secondary sample fixed effect regression estimation results for the loss ratios and indemnities per net planted acre are given in Tables 12-13.

Table 12 Cloud seeding effect on loss ratios for wheat and barley in the secondary sample (1989-2018), fixed effect regressions

	Wheat Loss Ratio	Barley Loss Ratio
Seeding	-0.785***	-0.607***
	(0.135)	(0.186)
Dry	0.505***	0.578***
	(0.0659)	(0.0872)
Wet	0.178***	0.194***
	(0.0335)	(0.0312)
GDD	-0.000163	-0.000143
	(0.000150)	(0.000170)
SDD	0.0162***	0.0139***
	(0.00323)	(0.00311)
Observations	1,491	1,489
R-squared	0.442	0.434

*** p<0.01, ** p<0.05, * p<0.1

Table 13 Cloud seeding effect on indemnities for wheat and barley in the secondary sample (1989-2018), fixed effect regressions

	Wheat Indemnity	Barley Indemnity
Seeding	-10.5*	-9.81*
	(5.66)	(5.10)
Dry	8.83***	6.11***
	(1.41)	(1.24)
Wet	3.54***	2.15***
	(0.631)	(0.549)
GDD	0.00257	0.000545
	(0.00200)	(0.00300)
SDD	0.217***	0.146***
	(0.0390)	(0.0380)
Observations	1,491	1,489
R-squared	0.596	0.591

*** p<0.01, ** p<0.05, * p<0.1

Again, results of the secondary sample equation estimations are like those from the primary sample. Cloud seeding tends to reduce loss ratios and indemnities. And the impact of cloud seeding on wheat and barley indemnities is statistically significant and of greater magnitude than in the primary sample. The estimated coefficients for $Seeding$ on wheat and barley loss ratios are statistically significant at the less than one percent level and much larger in magnitude compared with the results from the primary sample.

Additionally, I also conduct two additional sensitivity analyses. First, I remove treated counties from the dataset one at a time to test sensitivity of the coefficient estimates to the omission of individual treated counties. I present these coefficients in Appendix B.

The county sensitivity analysis reinforces the previous results. Cloud seeding has a strong positive relationship with wheat and barley yields, and a strong negative relationship with crop insurance outcome variables for the same crops. From this analysis, one can infer that Burke

County and Williams County drove some of the results in the main analysis. Williams County joined the program and 1997 and Burke County joined in 2015. The coefficient estimates reported are less significant after Burke is dropped, and more significant when Williams is dropped. This might imply that when data from Burke County is included the estimation of the cloud seeding effect is more precise, but it is unclear as to exactly why this might be.

The second sensitivity analysis looks at the coefficient estimates on $Seeding$ in the wheat yield regression models in different time intervals. As variation in program participation from 1989 to 2018 was low, the robustness check is conducted in order to introduce more variation in program participation over different time periods. The coefficient estimates and number of changes in the cloud seeding treatment are presented in Appendix B.

The coefficient estimates reported for $Seeding$ are smaller than the those reported in the 1989 to 2018 wheat yield models. The 1989 to 2014 interval was the only other interval with a statistically significant estimated coefficient. However, the estimates may be the result of program improvement over time. Over the years, the NDARB has made significant improvements in their cloud seeding operational effectiveness. In 1996 the NDARB purchased three WSR-74C radars; in 1998 Thunderstorm Identification Tracking Analysis and Nowcasting (TITAN) software was incorporated into project operations on radars; in 2003 all Piper Twin Comanche aircraft were replaced with Piper Seneca IIs, improving fuel and load capacity; and in 2010 they replaced the Cessna 340 with a Piper Cheyenne II turbo-prop aircraft, which vastly improved response time and payload capacity (Schneider et al., 2011). It is not surprising that the main effects of participating in NDCMP are stronger in the 1989-2018 sample period because of the aforementioned improvements.

4.4 Benefit-Cost Analysis of the NDCMP

The purpose of this examination is to determine the degree to which cloud seeding treatment mitigates crop damages in North Dakota. Benefit-cost calculations based on the results can prove helpful in understanding the value of the NDCMP program to the farmers and insurance providers of North Dakota, and the state.

Other researchers have considered the value of crops potentially savable through cloud seeding (Bangsund & Hodur, 2019; Bangsund & Leistritz, 2009; Smith et al., 1992). The present study provides estimates of yield improvements for wheat due to cloud seeding treatment, which can be used to calculate some monetary benefits of the program.

Using data containing historical program costs from 2003 to 2018, USDA crop data, and the estimate presented earlier, the net present value (NPV) of the program in 2003 is estimated as follows:

$$NPV_{2003} = \sum_{t=1}^{16} \frac{B_t - C_t}{(1+\delta)^t} \tag{13}$$

Where $B_t - C_t$ represents the difference between benefits and costs accrued in time period t, and δ is the uniform discount rate assumed in the equation.

Cost (C_t) data for each year was provided by the NDARB, and includes the total cost shared by both the state and the participating counties in that time period. Assuming program costs are exhaustive, and negative externalities are minimal, the historical cost figures represent the total cost of the program in any given year. From 2003 to 2018 the program had an average cost of $815,771 per year.

Recall that crop yield is calculated by dividing the bushels of crop produced by harvested acres in any given county. Thus, the coefficient estimates for the wheat yield model results imply that a county participating in the program has yields that are 3.87 bushels of wheat per harvested acre more than a similar county that does not participate in the program, on average.

Benefits (B_t) for each time period are calculated multiplying the estimated coefficient (3.87) by the total harvested acres in counties participating in the program and the price per bushel for wheat in any given year. Market year spring and durum wheat price data were collected from the same NASS database where crop yield data was obtained.

The matter of the selecting the appropriate discount rate (δ) is one of debate. Two of the main approaches toward estimating the discount rate are the social rate of time preference and the social opportunity cost of capital methods. The former assumes that per capita consumption dictates social welfare outcomes, and the latter tries to determine the government's opportunity cost of borrowing by taking the weighted average of (i) the production rate of interest, (ii) the consumption rate of interest, and (iii) the marginal rate of return for foreign investments (Broughel & Valdivia, 2018). Moore and Vining (2018) use the first method to conclude that a discount rate somewhere around 3.5 percent is appropriate, whereas Burgess (2018) leverages the second method to arrive at a rate closer to seven percent. For the sake of simplicity in this study, separate NPV estimates are calculated using both the 3.5 percent and seven percent discount rates. Although, constant discount rates are not necessarily correct. An increasing or decreasing discount rate can lead to much lower or higher NPV estimates. Still, discounted benefit to cost ratios are relatively unaffected if both benefits and costs are discounted evenly.

Following the procedure above, the NPV of the NDCMP in 2003 was somewhere between \$268 million and \$343 million (see Appendix C for a more detailed table of values used in this NPV calculation). And the discounted benefit to cost ratio was between 36:1 and 37:1. Benefits exceeded costs in every year under analysis. Similar benefit-cost ratios are reported in the literature, but none have leveraged estimates using a fixed effects regression estimation framework. Such benefit-cost ratios appear very favorable, and they do not consider the likely additional benefits the program accrues by reducing hail damage to other crops, automobiles, residential and commercial properties, etc.

Bangsund and Hodur (2019) estimate that the NDCMP increases annual wheat yields from anywhere between 1.47 and 2.90 bushels per harvested acre for treated counties. My estimate of 3.87 bushels per harvested acre is higher than those estimates perhaps because it is not explicitly based on precipitation enhancement scenarios and captures part of the hail suppression program effect. Their estimates were made based on hypothesized increases in beneficial precipitation (five percent or ten percent increase scenarios) and with wheat being composed of winter, spring, and durum varieties. Following my outlined procedure, their estimates roughly imply the NPV of the NDCMP in 2003 was somewhere between $97 million and $255 million (depending on the discount rate or yield increase used in the calculation).

CHAPTER 5: CONCLUSIONS

5.1 Cloud Seeding Effects

This study finds evidence that the NDCMP effectively improves wheat yield outcomes in participating counties of North Dakota as evidenced by the statistically significant effect of cloud seeding on wheat yield in the primary crop yield model, and the statistically significant effect of cloud seeding on wheat insurance loss ratios.

Given that NDCMP aircraft pilots target storms for cloud seeding before they have reached a participating county, it is possible that counties surrounding those which participated in the NDCMP program also have some indirect benefit from the program. Thus, estimating a significant program effect comparing seeded counties with adjacent non-treated counties suggests that the true impact may be larger than those presented in this study.

I also conducted sensitivity analysis using alternative model specifications using alternative time periods and county samples, and nearly all of them generated estimated coefficients with the same signs. Recall that when a sample of all North Dakota counties is used the economic and statistical significance of cloud seeding improved. As discussed in Chapter 3, this secondary sample is likely to have generated an overestimate of the effect of the cloud seeding treatment effect on small grain crop yields.

A benefit-cost analysis of the NDCMP shows that the discounted benefit-cost ratios associated with program participation likely lies between 36:1 and 37:1. The estimated benefits incorporated into the analysis are conservative in that they do not consider the program’s impact on mitigating additional crop damage, property damage, or automobile damage.

Benefits appear to accrue primarily to farmers and insurers in participating counties, with all taxpayers being burdened with the program costs. Spillover effects, where neighboring counties gain a marginal benefit from the program, are likely to exist with a program such as the NDCMP. Researchers employing spatial econometric methods may be able to measure those spillover effects. However, without exploring the potential impacts of cloud seeding in reducing automobile and property losses, it is unclear exactly how much taxpayers stand to benefit from the program. Aggregate shifts in the economy due to changes in crop supply and consumer spending could also potentially compensate taxpayers in an indirect way, but such subtle changes are difficult to measure and interpret.

The moral or philosophical questions associated with altering the weather could be discussed, but I make no effort to do so, and provide an impartial analysis of the program. While some residents in the state are against the NDCMP on grounds of lacking scientific evidence, the results presented here suggest that program participation is generally correlated with improved wheat yield outcomes and reduced losses.

Why might farmers lack interest in pushing for more cloud seeding research and implementation if they stand to benefit? One possible explanation is that that farmers might not care to support participation in the program because of increasingly generous incentives provided by the federal crop insurance program over the years. Such a moral hazard would leave farmers uninterested in wasting time to support the NDCMP, given that most of them have insurance and their losses are usually covered. More research is required to determine the extent to which the NDCMP has resulted in reductions in insurance premium costs over time.

5.2 Limitations

One of the biggest limitations of this study is the lack of data on the number of cloud seeding treatments and treatment intensity for a given county in a given year. Some years experience more hailstorm development than others, and it follows that the NDCMP aircraft pilots are more active during those years and might treat more potentially hail-producing clouds. Without being able to control for the differences in seeding frequency and intensity across counties and time, the analysis is hindered greatly.

Importantly, it should be recognized that program participation was not randomized across the state over time. Counties chose to opt into the program based on factors such as their budgets, various levels of small grain crop production, political beliefs, susceptibility to hail damage, etc.

If counties which stand to gain more from the program – those which suffer more perniciously from crop losses due to hail, and have the funding to participate – are the same ones which choose to opt-in, then it is quite likely that the estimated coefficients on the cloud seeding variable are biased upward in the crop yield model estimations. Counties which have the budget to afford the cloud seeding treatment, may also have the capacity to take additional measures to mitigate damage to crops in other forms (e.g., pest management). Some of this bias is addressed by the design of the primary sample where counties were included with similar weather characteristics and exposure to storms. Including counties in Montana and South Dakota, which have no access to the program, but similar characteristics to counties in western North Dakota, the primary crop yield model cloud seeding coefficients were less practically large than the secondary model coefficients.

Unfortunately, this study is unable to state whether or not the NDCMP has a causal effect on hail damage reduction. All one can infer is that counties participating in the program have higher wheat yields and lower loss ratios for wheat following program implementation than those that do not, holding some other variables fixed. Also, in order to better understand the direct effect of the program on hail suppression, more precise insurance data is needed. The SOB data used in this study is somewhat imprecise as it encompasses all insurance outcomes from January to December of any commodity year, and labels winter, spring, and durum wheat as "wheat." This represents a deviation in accuracy which can be greatly improved upon.

Regardless of these limitations, the evaluation presented in this study provides a new and arguably superior analysis of the cloud seeding program relative to previous studies.

5.3 Further Research

In this study, I use panel data analysis in an effort to isolate the effect of cloud seeding on small grain crop yields and insurance outcomes. With little access to reliable, long-term hail data, it is difficult to estimate the direct effect of cloud seeding on hail likelihood, magnitude, or frequency. Moreover, due to the fact that counties choose to participate in the NDCMP, there is a potential for self-selection bias, which makes it challenging to accurately estimate the effect of cloud seeding crop yields.

The underlying conditions which allow participating counties to benefit from the program appear to relate to temperature and precipitation patterns in those counties, so one cannot justify using the results of this paper to infer how cloud seeding would affect other areas of the country.. Even so, it may be that counties that have similar weather patterns to those participating in the NDCMP might stand to benefit a great deal by implementing a similar cloud seeding program.

The benefit-cost analysis alludes to strong incentive to experiment with cloud seeding in other areas of the country.

To investigate federal crop insurance outcomes more closely, researchers should check the RMA cause of loss data that links indemnity payouts to hail damage. Though promising, even with such data, one is only investigating a subset of generic crop insurance outcomes – where all wheat varieties are categorized under a single label – tied to hail (as the majority of policies are written privately). If one could obtain crop variety-specific private insurance data, it could be helpful for understanding how different types of wheat are affected by hail and other extreme weather outcomes.

One might explore a broader assortment of cloud seeding projects. There are more long-term cloud seeding projects which may offer prospects for economic analysis. For instance, the United Arab Emirates have been clouding seeding for enhanced precipitation since the early 1990s, the Alberta Hail Suppression Project has been ongoing since 1996, and the West Texas Weather Modification Association has been conducting cloud seeding activities to reduce drought since 2004. Though those programs do not likely randomize seeding treatment, there may be more variation in treatment over time or more opportunity to control for factors that might influence the decision to participate.

However, it is not simply long-standing programs which warrant further possibilities for useful research. In China, the largest weather modification project (possibly at a level which might be considered geoengineering) is being undertaken on the Tibetan Plateau. The project, called “Sky River”, aims to use ground-based cloud seeding methods to increase rainfall by up to 10 billion cubic meters per year (Nace, 2018). The project may not just enhance rainfall for China, but it may also increase flooding downstream on the Brahmaputra River which cuts through many Indian villages (Pathak, 2018). Clearly, the economic and political consequences of weather modification projects are not fully understood. Hopefully, data from the projects like "Sky River" will be made available. If they are not, researchers might still be able to conduct analyses of the benefits and costs of such projects.

As concerns about climate change continue to grow, weather modification efforts aiming to reduce damages from severe weather or enhance rainfall may grow. While such programs are not absolute solutions to issues related to the ever-changing climate, they do offer potential for human ingenuity to react and adapt to the problems being faced today.

APPENDICES

Appendix A Primary Sample County List

Table A1 List of counties included in the primary sample (1989-2018)

State	County
North Dakota	Adams
North Dakota	Billings
North Dakota	Bowman
North Dakota	Burke
North Dakota	Divide
North Dakota	Dunn
North Dakota	Golden Valley
North Dakota	Hettinger
North Dakota	McHenry
North Dakota	McKenzie
North Dakota	Mclean
North Dakota	Mountrail
North Dakota	Renville
North Dakota	Slope
North Dakota	Stark
North Dakota	Ward
North Dakota	Williams
Montana	Carter
Montana	Fallon
Montana	Richland
Montana	Roosevelt
Montana	Sheridan
Montana	Wibaux
South Dakota	Harding
South Dakota	Perkins

Appendix B Further Robustness Checks

Table B1 Sensitivity analysis results (seeding coefficient estimate reported)

Omitted County	Yield		Loss Ratio		Indemnity	
	Wheat	Barley	Wheat	Barley	Wheat	Barley
Bowman	3.73**	4.59	-0.623*	-0.218	-11.1	-9.41
Mountrail	3.74**	4.10	-0.547	-0.227	-9.63	-9.07
McKenzie	3.87**	4.30	-0.558*	-0.229	-9.67	-9.05
Ward	3.69**	4.10	-0.547	-0.237	-9.93	-9.31
Burke	3.15	-0.593	-0.172	0.134	1.03	0.149
Slope	3.20**	3.64	-0.740***	-0.349	-11.9	-9.86
Williams	6.06***	10.3**	-0.508	-0.416	-14.3	-16.3**

*** p<0.01, ** p<0.05, * p<0.1

Table B2 Time sensitivity analysis results (seeding coefficient estimates and robust standard errors reported)

Time Period	Wheat Yield	Number of Changes in Program Participation	*N*
1969 - 2018	0.797	10	1,187
	(0.918)		
1979 - 2018	1.52	9	937
	(1.33)		
1989 - 2018	3.87**	6	688
	(1.59)		
1989 - 2014	3.84**	5	620
	(1.86)		
1989 – 2005	3.34	5	425
	(2.41)		
1979 – 2014	1.48	8	869
	(1.10)		
1979 – 2005	1.35	8	674
	(1.11)		
1969 - 2014	0.0508	9	1,119
	(0.829)		
1969 - 2005	0.657	9	924
	(0.872)		

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Appendix C Benefit-Cost Analysis: Calculation Values

Table C1 Values used in calculation of 2003 NPV of the NDCMP ($ in 000's)

Date	Average Wheat Price Per Bushel[a]	Program Cost	Program Benefit	Harvested Acres of Wheat in Participating Counties	Discounted Benefit (3.5%)	Discounted Benefit (7%)	Discounted Cost (3.5%)	Discounted Cost (7%)	NPV (3.5%)	NPV (7%)
2003	3.75	616	21,611	1,490	20,880	20,197	595	576	20,285	19,621
2004	3.54	637	19,175	1,402	17,900	16,748	595	557	17,305	16,192
2005	3.50	648	19,844	1,465	17,898	16,198	584	529	17,314	15,670
2006	4.54	665	26,349	1,502	22,961	20,101	580	508	22,382	19,594
2007	9.23	697	53,170	1,490	44,767	37,909	587	497	44,180	37,412
2008	8.12	677	49,199	1,567	40,023	32,783	551	451	39,473	32,332
2009	4.83	731	27,910	1,495	21,937	17,381	575	455	21,363	16,926
2010	6.56	801	40,599	1,600	30,831	23,629	609	466	30,223	23,162
2011	8.81	774	29,515	866	21,656	16,054	568	421	21,088	15,633
2012	8.03	852	35,684	1,149	25,297	18,140	604	433	24,693	17,707
2013	6.83	962	16,133	611	11,050	7,664	659	457	10,391	7,207
2014	7.21	1,054	34,394	1,234	22,761	15,271	697	468	22,064	14,803
2015	5.61	979	23,197	1,070	14,832	9,626	626	406	14,206	9,220
2016	5.12	988	18,141	917	11,207	7,036	611	383	10,597	6,652
2017	5.86	951	23,616	1,042	14,096	8,559	568	345	13,528	8,215
2018	4.98	1,019	25,054	1,302	14,449	8,487	588	345	13,861	8,141
Total		13,052	463,589	20,199	352,547	275,785	9,595	7,297	342,952	268,488

Note[a] - Market year average wheat price data based on average of spring and durum wheat prices, not presented in 000's

REFERENCES

REFERENCES

Bangsund, D. & Leistritz L. (2009). Economic impacts of cloud seeding on agricultural crops in North Dakota [PDF file]. Retrieved from https://www.semanticscholar.org/paper/Economic-Impacts-of-Cloud-Seeding-on-Agricultural-Bangsund-Leistritz/bebd8ba7a71ab744340887e76f0672d5895a762d

Bangsund, D. & Hodur, N. (2019). Economic impacts of cloud seeding on agricultural crops in North Dakota. *Agribusiness & Applied Economics Report, No. 791*. https://doi.org/10.22004/ag.econ.291806

Broughel, J., & Valdivia, W. (2018). Three approaches to the social discount rate, presented at Mercatus Symposium, Arlington, 2018. Arlington, VA: Mercatus Center at George Mason University.

Burgess, D.F. (2018). The appropriate measure of the social discount rate and its role in the analysis of policies with long-run consequences, presented at Mercatus Symposium, Arlington, 2018. Arlington, VA: Mercatus Center at George Mason University.

Butchbaker, A.F. (1970). Results of the Bowman-Slope hail suppression program [PDF file]. Retrieved from http://hdl.handle.net/10365/24559

Changnon, S.A. (1962). Areal frequencies of hail and thunderstorm days in Illinois. *Monthly Weather Review*, 519-524. https://doi.org/10.1175/1520-0493(1962)090<0519:AFOHAT>2.0.CO;2

Changnon, S.A. (1967). Areal-temporal variations of hail intensity in Illinois. *Journal of Applied Meteorology*, *6*, 536-541. https://doi.org/10.1175/1520-0450(1967)006<0536:ATVOHI>2.0.CO;2

Changnon, S.A. (1969). Hail measurement techniques for evaluating suppression projects. *Journal of Applied Meteorology*, *8*, 596-603. https://doi.org/10.1175/1520-0450(1969)008<0596:HMTFES>2.0.CO;2

Changnon, S.A. (1977). On the status of hail suppression. *Bulletin of the American Meteorological Society*, *58(1)*, 20-28. https://doi.org/10.1175/1520-0477(1977)058<0020:OTSOHS>2.0.CO;2

Changnon, S.A. & Stout, G.E. (1967). Crop-hail intensities in central and northwest United States. *Journal of Applied Meteorology*, *6*, 542-548. https://doi.org/10.1175/1520-0450(1967)006<0542:CHIICA>2.0.CO;2

Che, Y., Feng, H., & Hennessy, D.A. (2020). Recency effects and participation at the extensive and intensive margins in the U.S. federal crop insurance program. *The Geneva Papers on Risk and Insurance – Issues and Practice, 45*, 52-85. https://doi.org/10.1057/s41288-019-00147-5

Crow, E.L., Long, A.B., Dye, J.E., & Heymsfield, A.J. (1979). Results of a randomized hail suppression experiment in northeast Colorado. Part II: Surface data base and primary statistical analysis. *Journal of Applied Meteorology*, *18*, 1538-1558. https://doi.org/10.1175/1520-0450(1979)018<1538:ROARHS>2.0.CO;2

Goodwin, B.K. (1994). Premium rate determination in the federal crop insurance program: What do averages have to say about risk? *Journal of Agricultural and Resource Economics, 19(2),* 382-395. https://www.jstor.org/stable/40986853

Hakala, K., Jauhiainen, L., Himanen, S.J., Rotter, R., Salo, T., & Kahiluoto, H. (2012). Sensitivity of barley varieties to weather in Finland. *Journal of Agricultural Science, 150,* 145-160. https://doi.org/10.1017/S0021859611000694

Hausle, E.A. (1972). Potential economic values of weather modification on Great Plains grasslands. *Journal of Range Management, 24,* 92-95. https://doi.org/10.2307/3896792

Johnson, J.E., Coon, R.C., & Enz, J.W. (1989). Economic benefits of crop-hail reduction efforts in North Dakota. *Agricultural Economics Report, No. 247.* Retrieved from http://www.swc.nd.gov/arb/ndcmp/pdfs/EconBen_CropHailRed_1989.pdf

Klink, K., Wiersma, J.J., Crawford, C.J., & Stuthman, D.D. (2014). Impacts of temperature and precipitation variability in the Northern Plains of the United States and Canada on the productivity of spring barley and oat. *International Journal of Climatology*, *34,* 2805-2818. https://doi.org/10.1002/joc.3877

Langerud, D. (2017). North Dakota cloud modification project [PDF file]. Retrieved from http://www.legis.nd.gov/files/committees/65-2017/19_5019_03000appendixg.pdf

Lanning, S.P., Kephart, K., Carlson, G.R., Eckhoff, J.E., Stougaard, R.N., Wichman, D.M., Martin J.M., & Talbert, L.E. (2010). Climatic change and agronomic performance of hard red spring wheat from 1950 to 2007. *Crop Science*, *50,* 835-841. https://doi.org/10.2135/cropsci2009.06.0314

Lemons, H. (1942). Hail in American agriculture. *Economic Geography*, *18(4)*, 363-378. https://doi.org/10.2307/141444

Lichtenberg, E. & Zilberman, D. (1986). The econometrics of damage control: Why specification matters. *American Journal of Agricultural Economics*, *68(2),* 261-273. https://doi.org/10.2307/1241427

Miller, J.R., Boyd, E.I., Schleusener, R.A., & Dennis, A.S. (1975). Hail suppression data from western North Dakota, 1969-1972. *Journal of Applied Meteorology, 14,* 755-762. https://doi.org/10.1175/1520-0450(1975)014<0755:HSDFWN>2.0.CO;2

Miller, J.R. & Fuhs, M.J. (1987). Results of hail suppression efforts in North Dakota as shown by crop hail insurance data. *Journal of Weather Modification, 19(1),* 45-49. Retrieved from https://www.journalofweathermodification.org/index.php/JWM/article/view/384

Moore, M.A., & Vining, A.R. (2018). The social rate of time preference and the social discount rate, presented at Mercatus Symposium, Arlington, 2018. Arlington, VA: Mercatus Center at George Mason University.

Nace, T. (2018). China is launching weather-control machines across an area the size of Alaska. Retrieved from https://www.forbes.com/sites/trevornace/2018/05/10/china-is-launching-a-massive-weather-control-machine-the-size-of-alaska/#6dff73f66315

Newell, H.E. (1966). A recommended national program in weather modification. *ICAS Report, No. 10a.* Retrieved from https://ntrs.nasa.gov/search.jsp?R=19680002906

North Dakota State Water Commission (n.d.). NDCMP History. Retrieved from http://www.swc.nd.gov/arb/ndcmp/

Pathak, S. (2018). Adding artificial rain to the Sino-Indian conundrum. Retrieved from https://asiatimes.com/2018/04/adding-artificial-rain-sino-indian-conundrum/

Reeves, D.L. (1979). The effects of simulated hail injury on oats. *Agricultural experiment station technical bulletins, 50.* Retrieved from http://openprairie.sdstate.edu/agexperimentsta_tb/50

Rose, R.L. & Jameson, T.C. (1986). Evaluation studies of long-term hail damage reduction programs in North Dakota. *Journal of Weather Modification, 18,* 17-20. Retrieved from http://journalofweathermodification.org/index.php/JWM/article/view/399

Schlenker, W. & Roberts, M.J. (2009). Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences of the United States of America, 106(37),* 15,594-15,598. https://doi.org/10.1073/pnas.0906865106

Schleusener, R.A. & Jennings, P.C. (1959). An energy method for relative estimates of hail intensity. *Bulletin of the American Meteorological Society, 41*, 372-376. https://doi.org/10.1175/1520-0477-41.7.372

Schneider, M.D. & Langerud, D.W. (2011). Operational improvement on the North Dakota cloud modification project. *Journal of Weather Modification,* 84-88. Retrieved from http://journalofweathermodification.org/index.php/JWM/article/view/151

Setter, T.L., & Waters, I. (2003). Review of prospects for germplasm improvement for waterlogging tolerance in wheat, barley and oats. *Plant and Soil, 253(1),* 1-34. https://doi.org/10.1023/A:1024573305997

Smith, P.L., Johnson, R.L., & Priegnitz, D.L. (1997). An exploratory analysis of crop hail insurance data for evidence of cloud seeding effects in North Dakota. *Journal of Applied Meteorology, 36(5),* 463-473. https://doi.org/10.1175/1520-0450(1997)036<0463:AEAOCH>2.0.CO;2

Smith, P.L., Johnson R.L., Priegnitz, D.L., & Mielke, P.W. (1992). A target-control analysis of wheat yield data for the North Dakota cloud modification project region. *Journal of Weather Modification, 24(1),* 1-38. Retrieved from http://journalofweathermodification.org/index.php/JWM/article/view/316

Smith, P.L., Miller, J.R., & Mielke, P.W. (1987). An exploratory study of crop-hail insurance data for evidence of seeding effects in North Dakota. *Report SDSMT/IAS/R-87/01.*

Sonka, S.T. & Potter, C.W. (1977). Evaluation of potential farmers benefits from hail suppression. *Western Journal of Agricultural Economics, 1(1),* 176-180. Retrieved from https://www.jstor.org/stable/40987911

Swanson, E.R., Huff, F.A., & Changnon, S.A. (1972). Potential benefits of weather modification for Illinois agriculture. *Illinois Agricultural Economics, 12(1),* 31-36. https://doi.org/10.2307/1348769

Tessendorf, S.A. (2019). A transformational approach to winter orographic weather modification research: The SNOWIE project. *Bulletin of the American Meteorological Society*, 71-92. https://doi.org/10.1175/BAMS-D-17-0152.1

USDA National Agricultural Statistics Service (2010). Usual planting and harvesting dates for U.S. field crops. Retrieved from https://usda.library.cornell.edu/concern/publications/vm40xr56k

USDA Risk Management Agency (2019). North Dakota crop insurance: State profile. Retrieved from https://www.rma.usda.gov/en/RMALocal/North-Dakota/State-Profile

Weather Modification Association (2009). WMA position statement on the environmental impact of using silver iodide as a cloud seeding agent [PDF file]. Retrieved from http://weathermod.org/

Weather Modification International (2019). North Dakota cloud modification project 2019 final operations report [PDF file]. Retrieved from http://www.swc.nd.gov/arb/ndcmp/

Wiersma, J.J. (2018). Late planting spring small grains. Retrieved from https://extension.umn.edu/planting-small-grains/late-planting-spring-small-grains

Wiersma, J.J. & Ransom, J.K. (2005). The small grains field guide. St. Paul, MN: University of Minnesota Extension Service.

Xu, Z., Hennessy, D.A., Sardana K., & Moschini, G. (2013). The realized yield effect of genetically engineered crops: U.S. maize and soybean. *Crop Science, 53(3)* 735–745. https://doi.org/10.2135/cropsci2012.06.0399