Cloud Seeding and Crops Yields: Evaluation of the North Dakota Cloud Modification Project

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

SIGNIFICANCE STATEMENT: The North Dakota Cloud Modification Project was established in 1951 to reduce severe hail damage and increase precipitation in specific counties in North Dakota. Every year, participating counties receive cloud-seeding treatment during the months of June, July, and August. We use the historical cloud-seeding participation to estimate the effect of cloud seeding on wheat and barley yields. In addition, we estimate the effect of cloud seeding on insurance losses for those same crops. Our evaluation indicates that the cloud-seeding program had significant positive effects on crop yields and improved loss ratios. The examination offers new evidence about the effectiveness of hail suppression through cloud seeding.

KEYWORDS: Atmosphere; North America; Hail; Regression analysis; Cloud seeding

1. Introduction

The objective of this paper is to conduct an evaluation of the North Dakota Cloud Modification Project (NDCMP). 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. Initially, 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 used to introduce a cloud-seeding agent (usually silver iodide) into 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 one potential benefit to farmers in western North Dakota, managing hailstorms is the program's primary objective. In 2019, approximately 80% of airtime was spent seeding clouds with the goal of mitigating hail damage (Weather Modification International 2019).

In the early years of the program, airborne cloud-seeding operations were paid for by farmers and ranchers across the state. In 1976, county participation soared as a state cost-share initiative was introduced (see Fig. 1). However, today just 6 of 53 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 and less hail than the western side.

While there were numerous studies on cloud seeding in the 1970s and 1980s, none offer a definitive assessment of effectiveness. The strengths and limitations of these studies are discussed later. In addition to offering a rigorous assessment of the program directly on crop yields, we investigate the effect of the cloud-seeding program on insurance loss ratios—defined as total indemnities paid to farmers divided by total premiums paid by farmers in a county in a given year as reported by the U.S. 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 and Hodur 2019). However, the researchers based their analysis of crop damage savings using a cloud-seeding hail-reduction factor of 45% as estimated by Smith et al. (1997). Our analysis does not rely on assumptions about the percentage of crop losses saved by cloud seeding, and instead examines the impacts directly from crop yield and insurance loss data.

Although some atmospheric studies have examined the efficacy of the treatment, few have used statistical procedures to determine how the program affected crop yields and crop losses. We use the panel nature of historical cloud-seeding participation and crop data to estimate a two-way fixed-effects regression with county-specific time trends to examine the effect of cloud seeding on wheat and barley yields. In addition,

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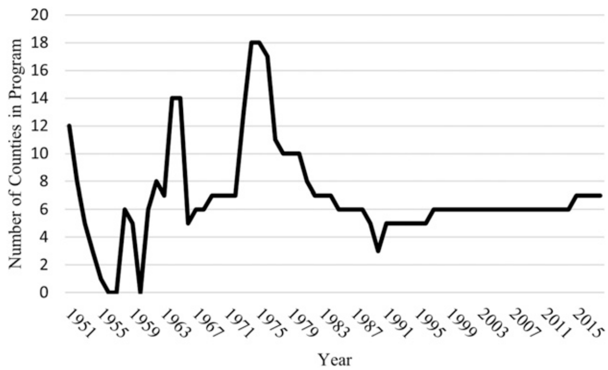

FIG. 1. Number of counties participating in NDCMP (1951–2018).

we use federal crop insurance data to estimate the effect of cloud seeding on losses for those same crops. As a prelude to the full analysis, our evaluation indicates that the cloud-seeding program had significant positive effects on crop yields and improved loss ratios.

The remainder of this paper is organized as follows. In the next section we offer a review of the literature on the history of cloud seeding, the role of crop insurance, and the most pertinent literature evaluating the impacts of cloud-seeding programs. The conceptual framework is presented in section 3. In section 4, we present the data and empirical approaches, and results are discussed in section 5. The final section contains conclusions.

2. Literature review

a. Cloud seeding

In 1948, when V. Schaefer and B. 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.

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 (glaciogenic 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 mitigated, thus rendering any falling hail less destructive and/or creating a greater amount of smaller hail. The program in North Dakota relies on a contractor, Weather Modification International, 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).

Hailstorm studies were first conducted in Illinois using U.S. Weather Bureau records starting in the 1950s (Changnon 1967). Those earlier studies provided the historical information on hail that proved to be useful in evaluating the efficacy of cloud seeding. Data published by Changnon (1962) was helpful for crop-hail damage insurers, so they provided funding for further research about hail across the United States (Changnon and Stout 1967). During this period, the Interdepartmental Committee of Atmospheric Sciences was given a recommendation by H. E. Newell, NASA Associate Administrator for Space Science and Application, 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, researchers conducted one of the first thorough evaluations of the early hail-suppression program in North Dakota. Citing the method developed by Schleusener and Jennings (1959), Butchbaker (1970) analyzed hailfall energy values, the frequency of hailstorm occurrence, precipitation, and cloud radar reflectivity. He found a 30%–60% reduction in hail intensity in the target area when 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 nonseed days.

Changnon (1977) published a status report of hail suppression across the globe (South Africa, Canada, Colorado, North Dakota, South Dakota, and Texas) in the *Bulletin of the American Meteorological Society*. He reported reductions in hail ranging between 20% and 48%, though most results were not statistically significant at the 5% level.

Other researchers conducted numerous studies about the impact of cloud seeding on total mass of hail in a given 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 10% significance level. However, 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 effects of seeding more accurately.

Since that time, additional work has been undertaken to measure hail damage reductions directly on crop yields and crop insurance loss ratios. Further, over time research methods used to evaluate cloud seeding have improved. As technological instruments and three-dimensional data processing advancements are made, projects such as the Seeded and Natural Orographic Wintertime Clouds: The Idaho Experiment (SNOWIE) have leveraged such advancements to evaluate the potential for cloud seeding to bolster precipitation, thus enhancing snowpack (Tessendorf 2019).

b. Crop yield and crop insurance

Pests, disease, and/or weather events can damage crops, all of which can potentially reduce yields. If cloud seeding reduces crop damage caused by hail, one would expect crop yields to improve when seeding is introduced. Moreover, if seeding increases beneficial precipitation, crop yields could also increase, especially when more precipitation is needed.

In his investigation, Hausle (1972) found favorable benefit–cost ratios for cloud seeding. His evaluation approach 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 0.5-in. (1 in. = 2.54 cm) increase in precipitation with the annual economic costs of operating a cloud-seeding program. Hausle found benefit–cost ratios ranging from 6.4:1 to 25.2:1.

Swanson et al. (1972) used ordinary least squares (OLS) regression to estimate the impacts of changing rainfall levels in Illinois between 1931 and 1968 on corn and soybean yields. 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 an economic surplus over most of the state.

North Dakota small grain crops suffer hail damage during different stages of their development, and thus crop insurance is of paramount importance to farmers in the region (Wiersma and Ransom 2005). Sonka and Potter (1977) estimated the possible benefits of hypothetical hail-suppression effectiveness for wheat farmers in the Great Plains region as wheat is particularly susceptible to hail damage. They then compared those benefits with other options available to farmers for reducing crop hail damage risks—such as hail insurance or all-risk insurance. Their results indicated that cloud seeding would need to reduce hail crop damage by 20% and increase rainfall by 10% in order to be more cost effective than insurance.

Following Miller and 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 45% lower than would be expected based on previous experience during the years 1976–88. However, the changes in the loss ratios could not be directly linked to hail damage.

Analyses of cloud-seeding effectiveness have focused primarily on the monetary benefits tied to increased crop yields or lower costs associated with decreased hail damage risk. Rose and 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 within the target and control areas. 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% loss reduction factor (Smith et al. 1987). The researchers estimated a 10-yr average annual savings of $3.8 million based on the value of crops saved from hail damage for the six treated counties over the 1976–85 period (Johnson et al. 1989).

Other researchers have evaluated the NDCMP's economic impact using more recent crop production and insurance data. However, these reports have assumed that the historical 45% hail reduction due to the program generates a 45% reduction in actual crop hail damage (Bangsund and Hodur 2019; Bangsund and Leistritz 2009).

Very recently, Rivera et al. (2020) offered a broad summary of research on hail-suppression activities globally that summarized findings from 194 published studies over the 1958–2019 period with the goal of informing the efficacy of the hail-suppression program in Mendoza, Argentina. Based on these studies, Rivera et al. (2020) conclude that there is still uncertainty in the quantitative effects of cloud seeding to suppress hail.

The present study examines the impact of program participation in North Dakota on wheat and barley yields and associated changes to crop insurance metrics. In our evaluation, if a county participated in the program in any given year, it will be considered part of the ‘‘seeded’’ or ‘‘treated’’ group for that year. That is, cloud seeding is measured by a binary variable equal to 1 if a county participated in the NDCMP program for a given year and 0 if it did not. Unfortunately, individual cloud-seeding treatment event data for each county and year are unavailable. 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 effects of cloud seeding. Our estimation procedure relies on the changes in cloud-seeding status to generate the estimated effects. That is, the cloud-seeding parameter estimate is generated from the within-county variation over time in cloud seeding and crop yields to generate the estimated impact.

In addition to examining the impacts of cloud seeding on crop yields, we also evaluate effects on loss ratios, and 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 (1 acre = 0.4 ha) 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 30-yr period between 1989 and 2018 to leverage available RMA crop insurance data in the state. Because the fixed-effects estimation approach we use relies on changes in treatment status to form the parameter estimate, it is important to note that seven changes in county program participation occurred—a county either entered or dropped out of the program a total of seven times. As shown in Fig. 2, the counties that received treatment at least once during the period are Bowman, Burke, McKenzie, Mountrail, Slope, Ward, and Williams.

The analyses 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. In the context of crop yield estimation, including time effects and county-specific time trends are important to control for improvement in farming practices, changing technology, and changing crop varieties over time. The inclusion of county fixed effects controls for differences across space as well. This estimation approach enables us to isolate the effect of cloud seeding. The primary sample of counties included in the evaluation is provided in Table 1. Bordering counties in Montana

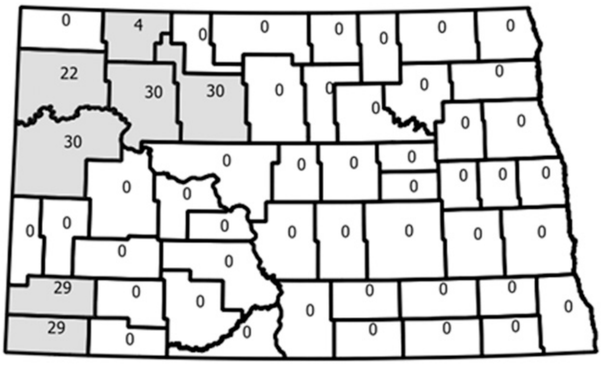

FIG. 2. Number of years for which a county participated in NDCMP (1989–2018).

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, which reduced concerns about sample selection bias. Previous research has also included counties in eastern Montana as part of the control group (Miller and Fuhs 1987; Smith et al. 1997).

To our knowledge, this is the first study of 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. In the next section, we present the conceptual framework that serves as a foundation for the empirical analysis.

3. Conceptual framework

As cloud seeding is conducted to reduce hail damage, counties that 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 (1986), cloud-seeding treatment enters a small grain crop yield damage abatement function as a damage control agent [Eq. (1)]:

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

where $Y^0_{ikt}(\mathbf{Z})$ is the minimum output for crop i in county k at time t given some vector of inputs $\mathbf{Z}$, and $Y^0_{ikt}(\mathbf{Z}) + Y^1_{ikt}(\mathbf{Z})$ represents the potential output. Also, $G_{kt}(X)$ is the damage abatement function, where $G_{kt}(X) = 1$ represents the 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 true 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 $X \to 1$. In this study, we test the hypothesis that cloud seeding will

TABLE 1. 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

increase the crop yield by reducing hail damage as illustrated by Eq. (2).

The general linear form shown in Eq. (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 from year to year. 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 within a 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 crop damages, it should also play some role in crop insurance premium rates, indemnity payments, and loss ratios. Additional theoretical modeling that is available from the authors upon request offers an examination of the degree to which losses, insurance indemnity payments, and premiums are affected by cloud seeding. To summarize, if cloud seeding reduces losses, then indemnities will also decline. However, the degree to which the drop in indemnities translates to lower insurance premiums is indeterminant. Thus, it is unclear to the degree to which cloud seeding will affect premiums and thus loss ratios. In our empirical analysis, we also test the hypotheses that (i) insurance indemnities will decline as a result of cloud seeding and (ii) loss ratios will fall. The impact of cloud seeding on premiums is not investigated here because of the complex nature of premium-setting calculations.

TABLE 2. 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
Avg precipitation (in.)	2.27	2.43	2.48	3.00
Avg temperature (°F; ≈0.5556 × °C)	63.8	63.2	63.2	63.7

4. Empirical analysis

a. Data sources

NDARB provided the NDCMP historical cloud-seeding data. The data include information about which counties participated in the NDCMP program from 1951 through 2018, and whether a county participated in a given year. We use a 30-yr subset of the data for this study. Border counties in Montana and South Dakota are included as part of the control group because of their proximity to the treated counties and their similarity in climatological patterns. In Table 2, we present a comparison of precipitation and temperature data between the treated counties in North Dakota and those bordering in Montana and South Dakota. Table 2 also offers a comparison of the western counties in North Dakota with those in the eastern side of the state, which are 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.

Wheat and barley yield data were obtained from the USDA National Agricultural Statistics Service (NASS).[1] NASS collects crop yield data through sample surveys. The surveys do not necessarily cover all farmers harvesting for every year, and thus the crop data are incomplete. 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 outcome reporting are not specified for the individual types of wheat, but for wheat in general. Table 3 provides summary statistics for these crops. Seeded counties have higher 30-yr average wheat and barley yields than nonseeded counties.

Crop insurance data starting in 1989 were obtained from the RMA and include such information as total indemnities, total premiums, and loss ratios associated with crops normally harvested in any given year.[2] As of 2019, the RMA insured 80% of planted barley acres and 99% 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 because they mention some policy component potentially linked to receiving protection from yield loss. Although the multiple peril crop insurance provided by the Federal Crop Insurance Corporation (FCIC) covers hail damage, most crop-hail policies are provided directly to farmers by private insurers outside of the federal crop insurance program. Thus, the RMA data used in this study represent a subset of the relevant crop-hail insurance information. Table 3 also provides summary statistics of the RMA Summary of Business (SOB) data for seeded and nonseeded counties over the period. Seeded counties appear to receive more indemnity payouts per insured acre and pay higher premiums than nonseeded ones over the 30-yr period, on average. However, nonseeded counties have significantly higher average loss ratios than seeded ones over the period.

Since the RMA crop insurance data are only available beginning in 1989, a subset of the NDCMP county participation data from 1989 through 2018 is used for the analysis. Precipitation and temperature are considered part of the vector of inputs affecting crop yields defined in Eq. (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 and Roberts 2009). Clouds are only suitable for cloud seeding if they exhibit a sustained updraft of moist air, thus we control for changes in drought severity (using the PZ) instead of changes in average precipitation. The PZ is derived from the NOAA Palmer drought severity index, which is calculated from a combination of precipitation, temperature, and soil moisture data. GDD represents the sum over growing season days between upper and lower temperature thresholds (0° and 29°C, respectively), whereas SDD represents the sum over growing season days above an upper threshold (30°C) where the photosynthesis process diminishes, thus hindering small grain crop development.[3]

GDD and SDD are calculated using station-level daily maximum and minimum temperature data provided by NOAA's Global Historical Climatology Network (GHCN).[4] The station-level data are transformed into county-level data by taking average daily temperatures for all stations within each county from May through August (coinciding with the crop growing season). County-level PZ values are obtained by transforming NOAA climate division-level data.[5] Following an established procedure, area intersections between climate divisions and counties are calculated, and then PZ values are weighted by county intersection areas (Che et al. 2020). PZ values may be interpreted as follows: PZ ≤ -2 indicates drought, PZ ≥ 5

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

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

[3] More detail on the formulation of GDD and SDD is provided in Che et al. (2020).

[4] Detailed data are available at ftp://ftp.ncdc.noaa.gov/pub/data/ghcn/daily/by_year/ (note that most internet browsers no longer allow direct access to ftp sites).

[5] Detailed data are available at https://www1.ncdc.noaa.gov/pub/data/cirs/climdiv/.

TABLE 3. Small grain crop descriptive statistics: seeded and nonseeded counties in primary sample (1989–2018). The sample sizes N for crop insurance outcomes are greater than for crop yield outcomes because NASS data are incomplete (and winter wheat is not included).

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

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

indicates flood conditions, and PZ = 0 represents neutral moisture conditions (Xu et al. 2013).

Consistent with Che et al. (2020), we evaluate dry and wet weather conditions separately by using PZ to generate

$$\mathrm{Dry}_{it} = \min(0, \mathrm{PZ}_{it}) \quad \text{and} \tag{3}$$

$$\mathrm{Wet}_{it} = \max(0, \mathrm{PZ}_{it}), \tag{4}$$

where PZ_{it} is the May–August average PZ value for county i during year t. With Dry_{it} and Wet_{it} defined by Eqs. (3) and (4), one can interpret increases in either variable with associated increases in dryness or wetness, respectively.

Limitations in availability of hail frequency and magnitude data make it infeasible to estimate the program's direct effect on hail over the 30-yr study period. The NOAA storm events database provides a general record of hail events in the United States, but because the events are reported by an observer network, the record is partial and cannot be fully trusted.

b. Small grain crop yield model

To investigate the impact of the NDCMP program on crop yields, we use a two-way fixed-effects regression framework to control for unobserved, time-invariant factors at the county-level that may bias the program participation decision (political majority, religious majority, etc.). We 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. As highlighted earlier, including time effects in the model controls for factors that change over the period that affect farming productivity across the entire region (fertilizer, drought resistant crops, machinery, farming practices, etc.). The county fixed effects control for difference across counties that influence productivity. We also include county-specific time trends to control for general county-specific changes in productivity over time. The explanatory variable of interest is the binary variable indicating whether a county was seeded in any given year. As noted earlier, counties that participated were not randomly assigned. Also, 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. The reduced form model is written as follows:

$$\begin{aligned} Y_{ikt} &= \alpha \mathrm{Seeding}_{kt} + \beta \mathrm{Dry}_{kt} + \delta \mathrm{Wet}_{kt} + \mathrm{GDD}_{kt} + \mathrm{SDD}_{kt} \\ &\quad + t_t + c_k + t_t \times c_k + \epsilon_{ikt}, \end{aligned} \tag{5}$$

where the dependent variable is the annual yield [calculated by total production in bushels (1 bushel = 0.035 m^3) divided by total harvested acres] of crop i in county k at year t. $\mathrm{Seeding}_{kt}$ is a binary variable taking on the value 1 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, $t_t \times c_k$ 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. 2014; Lanning et al. 2010; Wiersma 2018) Thus, we expect that an increase in SDD will reduce yields and GDD will increase yields. Increased moisture levels could have a positive or negative effect depending on the timing of rainfall changes; increases

TABLE 4. Summary of variables: primary sample crop yield and insurance models.

Variable	Variable definition (units)	Mean (std dev)	Expected effect
Dependent			
Wheat yield	Bushels per harvested acre	29.0 (8.12)	
Barley yield	Bushels per harvested acre	44.2 (13.0)	
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 variables			
Dry	Negative min among 0 and the PZ value	0.696 (0.939)	−
Wet	Max among 0 and the PZ value	1.07 (1.58)	±
GDD	May–August growing degree-days	2104 (147)	+
SDD	May–August stress degree-days	42.2 (37.9)	−

earlier in the season may increase yields, whereas additional rainfall later in the season may result in waterlogging and decrease yields (Hakala et al. 2012; Setter and Waters 2003). Last, as plants require sufficient moisture to properly develop, we expect dry weather conditions will negatively affect yields.

c. Crop insurance model

As with the crop yield model, a parallel 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 illustrated by

$$I_{ijkt} = \alpha \text{Seeding}_{kt} + \beta \text{Dry}_{kt} + \delta \text{Wet}_{kt} + \text{GDD}_{kt} + \text{SDD}_{kt} + t_t + c_k + t_t \times c_k + \epsilon_{ikt}. \quad (6)$$

Equation (6) follows the same variable labeling convention as Eq. (5) with an exception. The dependent variable I_{ijkt} specifies the insurance outcome of interest, indicated by the subscript j, being explained in each regression. The insurance 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. All the regressions are estimated with robust standard errors.

Table 4 presents definitions and hypothesized effects of the variables that appear in the crop insurance regressions. 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. Cloud seeding should have a negative effect on loss ratios because indemnities are expected to decrease faster than premiums. Increases in GDD, SDD, and Dry are expected to have effects of opposite sign to those presented in Table 4, whereas Wet is indeterminant.

d. Robustness checks

Aside from generating estimates from the primary sample as described earlier, a secondary sample composed of all 53 counties in North Dakota is used to investigate the effect of program participation in a single state. 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 policies and other factors. Given that counties put participation in the program to a vote, the model estimates from the secondary sample may be biased upward. These estimates are presented in the robustness estimation subsection of the paper. Counties that choose to join the program may be those that expect to gain the greatest benefit, and so any apparent gains generated 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 the coefficient estimates could be sensitive to the omission of some counties that have a relatively large influence. To investigate this possibility, we evaluate how coefficient estimates change when specific counties are individually dropped from the sample. Thus, we estimate a set of regressions seven times (one for each dropped county) with augmented samples. These estimates are presented in section 5c.

Because of limited variation in program participation over the 1989–2018 period, we examine the sensitivity of our estimates to the choice of time period. Seeding coefficient estimates from the wheat yield model are obtained using the same core specification, but over differing time periods. Starting with the period from 1949 to 2018, robustness of the seeding coefficient estimate is examined in 10-yr increments, ending with the original period starting in 1989. Then, the same procedure is followed starting with the period from 1949 to 2014. These estimations are also presented in section 5c.

5. Empirical results

We begin the results section with a discussion of Figs. 3–6. These figures contain time series information for seeded and nonseeded counties in our primary sample from 1989 to 2018 for wheat yields (Fig. 3), wheat loss ratios (Fig. 4), and wheat

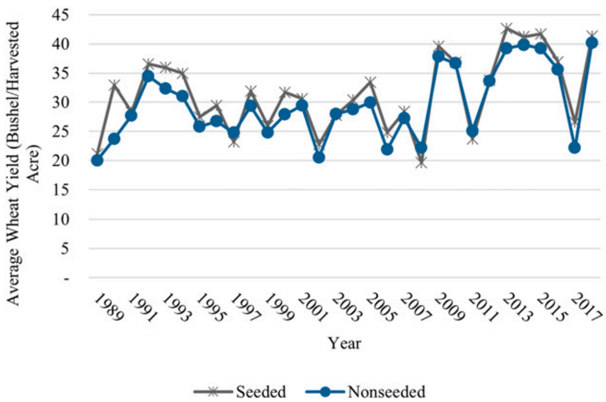

FIG. 3. Seeded and nonseeded county wheat yields.

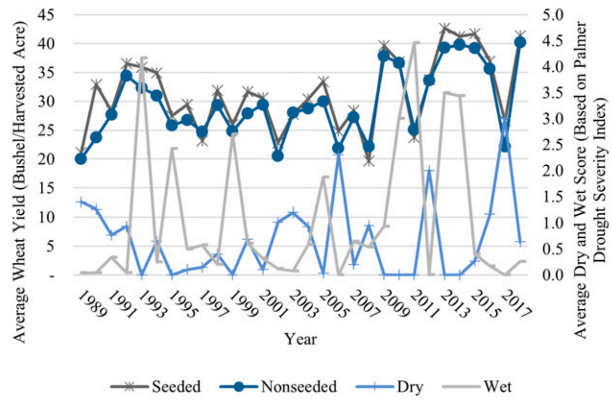

FIG. 5. Seeded and nonseeded county wheat yields as in Fig. 3, with average wet and dry scores added to the plot.

yields and wheat loss ratios with the measures of Wet and Dry overlayed (Figs. 5 and 6, respectively). These figures offer an overall comparison of trends for seeded versus nonseeded counties. While seeded and nonseeded wheat yield and wheat loss ratios fluctuate together, seeded counties had lower losses in 21 of the 30 years. Also, note that some of the spikes in wheat losses appear to be partially explained by unusually dry (drought) or unusually wet (flood) conditions. These graphs provide context for the regression analysis that seeks to isolate the effect of cloud seeding while controlling for a range of other factors.

a. *Small grain crop yield estimation*

Table 5 (columns 1 and 2) 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 hypothesized, the relationship between the cloud-seeding treatment and small grain crop yield is positive for both crops. However, the cloud-seeding effect on barley is statistically insignificant. These results show that counties participating in the NDCMP program grow 3.87 bushels more of wheat per harvested acre than counties not participating. Over the 30-yr period, the average wheat yield was approximately 28.98 bushels per harvested acre, so that participating counties' wheat yields are about 13% higher than nonparticipating counties.

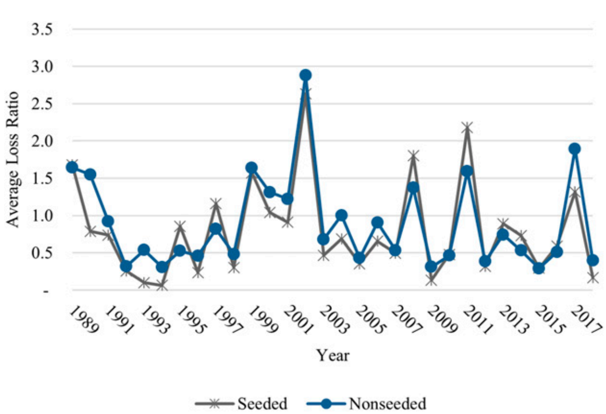

FIG. 4. Seeded and nonseeded county wheat loss ratios.

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 statistically insignificant in estimating crop yields on the margin, SDD is negative and statistically significant.

b. *Crop insurance estimation*

In Table 5 (columns 3–6), we also present results for the crop insurance loss ratio and indemnity models. The relationship between cloud-seeding treatment and small grain crop insurance loss ratios is significant and negative for wheat at the 10% significance level. Counties participating in the NDCMP have loss ratios related to wheat about 0.548 lower than counties that do not, on average. This finding is consistent with the idea that cloud seeding affects wheat indemnities more than premiums in the short term. Moreover, results suggest that insurers and the FCIC accrue a benefit from cloud seeding. 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. The cloud-seeding treatment has a negative estimated effect on indemnity payments for both wheat and barley, but neither coefficient is statistically significant. However, 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 through August is estimated to have a significant and positive impact on indemnity payments for wheat and barley. The nearly insignificant estimated coefficients associated with changes in GDD or SDD are indicative that indemnity payouts are linked with weather phenomenon that are stochastic and devastating in nature (like hail). However, the statistically significant coefficient on GDD is contradictory to our expectation. The unexpected coefficient on GDD could be the result of growing degree-days (when temperature is within an ideal growing range) being correlated with hail and other devastating

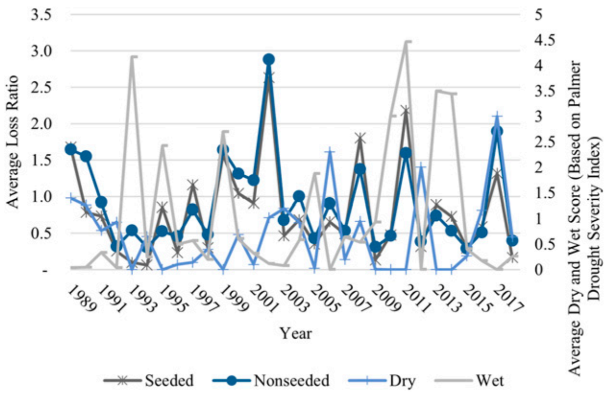

FIG. 6. Seeded and nonseeded county wheat loss ratios as in Fig. 4, with average wet and dry scores added to the plot.

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 support to the hypothesis that cloud-seeding treatment is correlated with reduced insurance loss ratios and indemnities paid by way of reducing crop damages in treated counties. However, the results for barley are statistically insignificant.

c. *Robustness estimation*

To examine the robustness of our core regression analysis, we estimate several different model specifications. First, we construct a secondary sample that includes all 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. Table 6 presents summary statistics for wheat and barley across the counties in the secondary sample. Unlike with the primary sample, in the secondary sample nonseeded counties have higher 30-yr average wheat and barley yields than the seeded counties. This difference supports the notion that there is a self-selection bias problem in the data whereby counties with lower average yields tend to opt into the NDCMP program because they suffer more significantly from hail damage.

In Table 6, we also present summary statistics for loss ratios, indemnities, and premiums across the counties in the secondary sample. As with the primary sample, 30-yr average loss ratios for wheat and barley are a good deal higher in the nonseeded counties. However, unlike the primary sample, 30-yr 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 nonseeded counties. In part, this could be because higher historical loss ratios in nonseeded counties drive premium prices more than does the average yield. Average barley losses could be worse in nonseeded counties because of differences in precipitation across the state, especially the eastern part, which tends to receive more rainfall.

As a further examination, we estimate several different model specifications. Secondary sample fixed-effects regression estimation results for the small grain crop yield models are presented in Table 7. The results largely corroborate the primary sample estimates. The relationship between cloud seeding and small grain crop yield is positive and statistically significant for wheat, but now at the 1% level, and positive for barley. The results imply that cloud-seeded counties gain 6.19 bushels of wheat per harvested acre more than nonseeded counties, all else held equal. The estimated coefficients for the weather variables (Dry, Wet, GDD, and SDD) are all of stronger significance. Interestingly, the estimated coefficient on Wet is negative for both crops, and statistically significant at the less than 1% level. This result is opposite of the primary sample estimates where the coefficient on Wet was positive. The reason for the change in sign is likely because the primary sample receives less rainfall than the secondary sample (see Table 2).

Secondary sample fixed-effect regression estimation results for the loss ratios and indemnities per net planted acre are also presented in Table 7.

The results from the secondary sample regression estimations are similar to those from the primary sample; cloud seeding tends to reduce both loss ratios and indemnities. Further, the impact of cloud seeding on wheat and barley indemnities is statistically significant and of greater magnitude than in the primary sample.

TABLE 5. Cloud-seeding effect on wheat and barley yields and insurance outcomes in the primary sample (1989–2018), with fixed-effect regressions. One, two, and three asterisks indicate significance levels of $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively. For each variable, the first row is the coefficient estimate and the second row is the standard error of the coefficient.

	Wheat yield	Barley yield	Wheat loss ratio	Barley loss ratio	Wheat indemnity	Barley indemnity
Seeding	3.87**	4.2	−0.548*	−0.231	−9.55	−9.02
	−1.59	−4.98	−0.316	−0.295	−7.86	−7.56
Dry	−3.12***	−5.38***	0.654***	0.576***	7.60***	4.58***
	−0.329	−0.553	−0.0451	−0.042	−1	−0.625
Wet	0.534*	−0.950*	0.0968**	0.0917**	0.0599	−0.805
	−0.296	−0.533	−0.0377	−0.0428	−0.888	−0.657
GDD	−0.001 75	−0.007 39	0.000 422	0.000 562	0.0244**	0.0132
	−0.002 02	−0.006 36	−0.000 45	−0.000 42	−0.0112	−0.0085
SDD	−0.009 40**	−0.0159***	0.001 91	0.001 87	0.0365	0.0292
	−0.004 22	−0.003 83	−0.001 68	−0.001 49	−0.0266	−0.0196
No. obs	688	597	743	742	743	742
R squared	0.731	0.749	0.529	0.578	0.619	0.692

TABLE 6. Small grain crop summer statistics (secondary sample): seeded and nonseeded counties (1989–2018).

Variable	Seeded: mean (std dev)	Nonseeded: mean (std dev)
	Wheat	
Planted (acres)	238 673 (129 966)	164 274 (98 291)
Harvested (acres)	230 334 (127 771)	158 249 (95 893)
Yield (bushels/harvested acre)	31.2 (8.06)	35.1 (11.7)
N	166	1312
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	1416
	Barley	
Planted (acres)	31 013 (24 120)	35 001 (34 076)
Harvested (acres)	27 839 (24 292)	32 930 (33 065)
Yield (bushels/harvested acre)	48.8 (12.5)	52.9 (13.7)
N	147	1179
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	1413

We also conduct two additional sensitivity analyses as further robustness checks. First, we remove treated counties from the sample one at a time to test sensitivity of the coefficient estimates to the omission of individual treated counties (we present these coefficient estimates in Table 8). 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. However, this evaluation also suggests that Burke and Williams Counties are influential in the main analysis. Williams County joined the program and 1997 and Burke County joined in 2015. The coefficient estimates reported are less significant when Burke is dropped, and more significant when Williams is dropped. When data from Burke County are included, the estimation of the cloud-seeding effect is more precise, but it is unclear as to why.

The second sensitivity analysis reconsiders the coefficient estimates on seeding in the wheat yield regressions using different time intervals. As variation in program participation from 1989 to 2018 was limited, this robustness analysis is offered 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 Table 9.

The coefficients for seeding are generally smaller than 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. One possible reason for reduced significance of the coefficient estimates is that the improvement in program effectiveness over time. Also note that during the earlier period of the program many counties adopted the program but then dropped it quickly, making estimation of the impacts difficult. Last, note that NDARB made significant improvements in their cloud-seeding operation over time. In 1996 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

TABLE 7. Cloud-seeding effect on wheat and barley yields and insurance outcomes in the secondary sample (1989–2018), with fixed-effect regressions. One and three asterisks indicate significance levels of $p < 0.1$ and $p < 0.01$, respectively. For each variable, the first row is the coefficient estimate and the second row is the standard error of the coefficient.

	Wheat yield	Barley yield	Wheat loss ratio	Barley loss ratio	Wheat indemnity	Barley indemnity
Seeding	6.19***	6.29	−0.785***	−0.607***	−10.5*	−9.81*
	−2.05	−4.33	−0.135	−0.186	−5.66	−5.1
Dry	−4.99***	−5.76***	0.505***	0.578***	8.83***	6.11***
	−0.471	−0.662	−0.0659	−0.0872	−1.41	−1.24
Wet	−0.784***	−1.77***	0.178***	0.194***	3.54***	2.15***
	−0.224	−0.321	−0.0335	−0.0312	−0.631	−0.549
GDD	0.001 84*	0.000 49	−0.000 163	−0.000 143	0.002 57	0.000 545
	−0.001 04	−0.001 77	−0.000 15	−0.000 17	−0.002	−0.003
SDD	−0.0833***	−0.105***	0.0162***	0.0139***	0.217***	0.146***
	−0.0185	−0.0206	−0.003 23	−0.00311	−0.039	−0.038
No. obs	1397	1261	1491	1489	1491	1489
R squared	0.742	0.716	0.442	0.434	0.596	0.591

TABLE 8. Sensitivity analysis results (seeding coefficient estimate reported). One, two, and three asterisks indicate significance levels of $p < 0.1$, $p < 0.05$, and $p < 0.01$, respectively.

	Yield		Loss ratio		Indemnity	
Omitted county	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**

Cheyenne II turbo-prop aircraft, which vastly improved response time and payload capacity (Schneider and Langerud 2011). It is possible that the main effects of participating in NDCMP are stronger in the 1989–2018 sample period because of these improvements.

d. *Benefit–cost analysis of the NDCMP*

Benefit–cost calculations based on the estimations results may prove helpful in understanding the value of the NDCMP program to the farmers, insurance providers of North Dakota, and the state as a whole. Other researchers have considered the value of crops potentially savable through cloud seeding (Bangsund and Hodur 2019; Bangsund and Leistritz 2009; Smith et al. 1992). The present study provides new estimates of yield improvements for wheat due to cloud-seeding treatment, which can be used to calculate some monetary benefits of the program.

Using historical program cost data from 2003 through 2018, USDA crop data, and the coefficient estimate on cloud seeding presented earlier, the net present value (NPV) of the program in 2003 is estimated using the following equation:

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

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.

TABLE 9. Time sensitivity analysis (seeding coefficient estimates, with robust standard errors in parentheses). Two asterisks indicate significance level of $p < 0.05$.

Time period	Wheat yield	No. of changes in program participation	N
1969–2018	0.797 (0.918)	10	1187
1979–2018	1.52 (1.33)	9	937
1989–2018	3.87** (1.59)	6	688
1989–2014	3.84** (1.86)	5	620
1989–2005	3.34 (2.41)	5	425
1979–2014	1.48 (1.10)	8	869
1979–2005	1.35 (1.11)	8	674
1969–2014	0.0508 (0.829)	9	1119
1969–2005	0.657 (0.872)	9	924

Cost (C_t) data for each year were provided by the NDARB and include the total cost shared by both the state and the participating counties. Assuming program costs are exhaustive, and negative externalities are minimal, the historical figures represent the total cost of the program for each year. From 2003 through 2018 the average annual cost was \$815,771.

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.

Benefits (B_t) for each time period are calculated by 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 NASS database.

The matter of selecting an appropriate discount rate δ is one of debate. Two options often used for discount rates are the social rate of time preference and the social opportunity cost of capital. The former assumes that per capita consumption dictates social welfare outcomes, whereas the latter is based on the government's opportunity cost of borrowing, which is 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 and Valdivia 2018). Moore and Vining (2018) apply the first approach, choosing a discount rate somewhere around 3.5%. Applying the second approach, Burgess (2018) chooses a rate closer to 7%. NPV estimates are calculated using both the 3.5% and 7% discount rates. However, in this case discounted benefit to cost ratios are relatively unaffected if both benefits and costs are discounted evenly.

Following the procedure above, the NPV of NDCMP was somewhere between \$268 million and \$343 million, with a discounted benefit-to-cost ratio between 36:1 and 37:1. Table 10 contains the more-detailed values used in this NPV calculation. Benefits exceeded costs in every year of our evaluation. Similar benefit–cost ratios for cloud seeding are reported in the literature. Note that our calculations are favorable even though they do not consider other possible benefits such as reduction in

TABLE 10. Values used in the calculation (as part of the benefit–cost analysis) of 2003 NPV of the NDCMP (in hundreds of dollars).

Date	Avg 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	1490	20,880	20,197	595	576	20,285	19,621
2004	3.54	637	19,175	1402	17,900	16,748	595	557	17,305	16,192
2005	3.50	648	19,844	1465	17,898	16,198	584	529	17,314	15,670
2006	4.54	665	26,349	1502	22,961	20,101	580	508	22,382	19,594
2007	9.23	697	53,170	1490	44,767	37,909	587	497	44,180	37,412
2008	8.12	677	49,199	1567	40,023	32,783	551	451	39,473	32,332
2009	4.83	731	27,910	1495	21,937	17,381	575	455	21,363	16,926
2010	6.56	801	40,599	1600	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	1149	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	1234	22,761	15,271	697	468	22,064	14,803
2015	5.61	979	23,197	1070	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	1042	14,096	8,559	568	345	13,528	8,215
2018	4.98	1,019	25,054	1302	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

[a] Market year average wheat price data are based on average of spring and durum wheat prices and are not presented in hundreds.

damages to other crops, automobiles, and residential and commercial properties.

6. Conclusions

In this study we present new evidence that cloud seeding improves wheat yield in participating North Dakota counties as evidenced by the statistically significant effect on wheat yields and insurance loss ratios. Sensitivity analysis using several model specifications, alternative time periods and county samples generated estimated coefficients with the same signs.

Discounted benefit–cost ratios associated with program participation is between 36:1 and 37:1. However, the estimated benefits are likely conservative in that they do not consider the program's impact on mitigating additional crop, property, or automobile damage. Discounted benefits appear to accrue primarily to farmers and insurers in participating counties, with all taxpayers being burdened with the program costs. Without exploring the potential impacts of cloud seeding in reducing automobile and property losses, the degree to which taxpayers stand to benefit from the program is unclear. 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.

A limitation of this study is the small number of cloud-seeding treatments over the period of analysis as well as lack of information on treatment intensity. In some years there are more hailstorm events than others, and it follows that NDCMP aircraft pilots are more active during those years and would treat more hail-producing clouds. Our evaluation is also hindered by lack of information on cloud-seeding frequency and intensity—though, there exists promising NOAA weather surveillance radar and reflectivity data that may help better understand the direct effect of cloud seeding on cloud attributes in the future.[6] It is important to recognize 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, and susceptibility to hail damage. If counties that stand to gain more from the program—those that suffer more from hail crop losses and have the funding to participate—are the same ones that choose to opt in, then the estimated coefficients on the cloud-seeding variable may be biased upward in the crop yield model estimations. This potential bias is addressed by the design of the primary sample where counties in Montana and South Dakota with similar weather characteristics were included. Despite these issues, our study provides a new and, in several respects, superior analysis of cloud-seeding programs.

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[6] For North Dakota these data were available from 1995 on, which would only allow us to observe one change in the status of cloud-seeding activity. Thus, this data source is not useful for evaluating the North Dakota hail-suppression program using the empirical strategy in this paper.

very helpful. Financial support for this research was provided by the USDA-funded North Central Regional Center for Rural Development (no specific project number).

Data availability statement. Data analyzed in this study were obtained from existing data that are openly available at locations cited in the reference section. Further documentation about data processing is available from the authors upon request.

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