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CLIMATE VARIABILITY AND WATER INFRASTRUCTURE:
HISTORICAL EXPERIENCE IN THE WESTERN UNITED STATES

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Climate Variability and Water Infrastructure: Historical Experience in the Western United States
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ABSTRACT

Greater historical perspective is needed to enlighten current debate about future human responses to higher temperatures and increased precipitation variation. We analyze the impact of climatic conditions and variability on agricultural production in five semi-arid western states. We assemble county-level data on dams and other major water infrastructure; agricultural crop mixes and yields; precipitation and temperature; soil quality, and topography. Using this extensive data set, we analyze the impact of water infrastructure investments on crop mix and yields in affected counties relative to similarly-endowed counties that lack such infrastructure. We find that water infrastructure smoothes agricultural crop production and increases the likelihood of a successful harvest, especially during times of severe drought or excessive precipitation.

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I. Introduction

There is a large and rapidly growing literature on climate change (Stern, 2007; Nordhaus, 2007; Weitzman, 2007 and references therein). Agriculture is particularly vulnerable to the impacts of climate change. For the U.S., the estimated impacts are often mixed, with findings of nonlinearities in key commodity yields beyond threshold temperatures; predictions of higher profitability for US agriculture; and reports of high adjustment costs (Mendelsohn, Nordhaus, and Shaw, 1994; Cline, 1996; Kelly, Kolstad, and Mitchell, 2005; Schlenker, Hanemann, and Fisher, 2006; Deschenes and Greenstone, 2007; Schlenker and Roberts, 2008). These climate change studies generally rely upon contemporary data or simulations. Greater historical perspective, however, would enlighten current debate about the effects of climate change and future human responses to it. Indeed, the expansion of agriculture across North America in the 19th and 20th centuries encountered greater climatic variation than is predicted under the current climate change models (Olmstead and Rhode, 2008). Accordingly, analysis of how those conditions were addressed historically and their impacts on crop mixes and agricultural production can provide valuable information for addressing current climate variability. This study adds to the literature on adaptation to climate fluctuation and change.

Much academic and policy concern has been focused on the mitigation of potential climate change through international efforts to control greenhouse gas emissions. Examples include the Kyoto Protocol and other national policies to implement cap and trade programs, as well as the shifting of energy production toward less-polluting sources, such as wind and solar power. Adaptation has received somewhat less attention. Yet, it is increasingly evident that adaptation must be given more consideration because the stock of greenhouse gasses may result in climate change regardless of mitigation efforts and because of the vulnerabilities of many of

the world's poorest societies. As Nordhaus observed, "mitigate we might; adapt we must."(Pielke, 1998).

The IPCC (2001) defines adaptation as the "adjustment in natural or human systems in response to actual or expected climatic stimuli or their effects, which moderates harm or exploits beneficial opportunities." In our study, we examine planned adaptation that involves deliberate policy decisions. Our specific concerns are water resources and the investment in infrastructure dedicated to irrigation that could help to mitigate the effects of more variable precipitation levels and periods of drought on agricultural production.

Agriculture is particularly sensitive to changes in water supplies. Water infrastructure investments in the United States in the 20th century, designed to address semi-arid conditions and drought (as well as flooding), provides a natural experiment to assess the impacts of such policies on agricultural production. The land west of the 100th meridian is North America's driest and has its most variable climate (Lettenmaier, et al., 2008). Further, there is an indication of increases in the duration and severity of drought in western regions (Andreadis and Lettenmaier, 2006). Concerns about the variability of water supplies in the West are not new – much of the present water supply infrastructure was constructed in the late 19th and early to mid 20th centuries due to historical demand for agricultural irrigation, flood protection, drinking water, and hydroelectric power. The extent to which this investment assuaged the impacts of climate instability is a focus of this study. Using historical county-level data for five western states, we examine if and how the water supply infrastructure stabilized agricultural production during droughts (and provided flood protection during periods of increased precipitation).

We construct an integrated dataset on water supply and water infrastructure in the states of North Dakota, South Dakota, Montana, Wyoming and Idaho. This county-level water

infrastructure dataset is spatially linked to topographic characteristics, historical climate data, and historical agricultural data. We use these data to analyze the impact of the water infrastructure on agricultural production, especially during times of drought or flood.

We find that counties that had water storage and distribution facilities were generally better able to deal with climatic variability. Farmers with access to more consistent water supplies were more likely to smooth their agricultural production (crop mix and yields) and had a higher likelihood of successful harvest, especially during periods of severe droughts and/or floods. Counties with water supply control were better able to mitigate losses in agriculture relative to similar counties without such infrastructure. Thus, our results indicate that the presence of major water infrastructure has helped to mitigate the damages of periodic droughts and floods, and will likely continue to do so in the future.

The remainder of this chapter is organized as follows: Section II provides a brief background on the origins of the water infrastructure in the western U.S., and lays out the questions examined in the paper. Section III describes data sources and the empirical strategies that were employed. Section IV summarizes the results of the empirical analysis, and section V concludes.

II. Origins and Impact of Western Water Infrastructure

During late 19th century, as agricultural settlement of North American moved into the Great Plains and beyond, irrigation expansion and flood control became crucial issues. The agricultural techniques and practices settlers brought with them from the humid East were not applicable in the arid or semi-arid West. Institutions such as the 1862 Homestead Act that created 160 to 320 acre small farms were not appropriate in the region (Libecap and Hansen,

2002). As early as the 1870s John Wesley Powell was promoting the organization of autonomous irrigation districts to promote cooperation among farmers and to cope with the externalities associated with each individual farmer's decision on water storage and distribution.

Interest in federal reclamation programs to construct dams and canals to store and distribute water developed after individual, corporate and state attempts to deliver such infrastructure was found to be inadequate. Many state attempts, such as the 1887 Wright Act of California, faced problems ranging from poor construction to the creation of fraudulent irrigation districts and the huge debts that ensued (Robinson, 1979). Most private irrigation projects failed, and those that succeeded were of small size due to problems of free-riding.

After much debate and failed attempts to develop water infrastructure in the West, the Federal Reclamation Act was passed in June 1902, and a revolving Reclamation Fund was created to finance water infrastructure projects. The Reclamation Fund was financed through the sales of public lands and through cost-sharing agreements by recipients (Pisani, 2002). The title for the water infrastructure remained with the federal government, state and territorial agencies; local water supply organizations, such as irrigation districts, governed the use and the distribution of water (Robinson, 1979). This structure mostly remains in place today.

In this chapter, we analyze the impact of this federal and related state and private water infrastructure on agricultural production and flood control over time using historical agricultural and climatic data. The specific research questions we seek to answer are:

- Were counties that had irrigation water supply and distribution infrastructure better able to cope with the problems of short-term climatic variability (either due to natural variability in the hydrologic cycle or due to disruptions of the cycle), relative to those similar counties without such infrastructure?

- Did cropping patterns (measured in area of irrigated and harvested land, relative to total agricultural land) change after the construction of irrigation water supply and distribution infrastructure?

- Did agricultural productivity (measured in crop-specific tons/acre or bushels/acre,) change after the construction of irrigation water supply and distribution infrastructure?

- Was the impact of water infrastructure on agricultural productivity and cropping patterns different (especially important) during periods of climate shocks of severe droughts and floods?

To address these questions, we examine the variation in agricultural production before and after dam and canal construction at the county level as well as across counties with and without such infrastructure. Counties with access to water infrastructure are likely to experience fewer agricultural production failures after unfavorable climatic conditions, all else equal. We also examine the variation in agricultural production in periods of normal precipitation and in times of droughts (and floods), across time.

III. Data and Empirical Model

In order to analyze the impact of dams on agricultural activities, we have compiled the most detailed data available on major water infrastructure, historical agricultural productivity and other relevant data, including the climate and geographic characteristics of our study area. Our empirical strategy focuses on five north-central states: Idaho, Wyoming, Montana, North Dakota and South Dakota (see: Map 1). Although there is variation within them, these five states are quite similar in annual temperature trends, precipitation, crops grown and soil types. However, within these states, the availability of irrigation water varies widely. Our sample includes all

counties in these states that are located west of the 100th meridian, generally considered the boundary between the dryer and wetter Great Plains; these counties, all of which are considered "arid" or "semi-arid", require additional irrigation in order to grow crops in a water-intensive fashion. We have 181 counties and a total of 3,620 observations, measured across 20 years (1900-2002) from the agricultural census.

The following sections describe our data sources, discuss the mechanisms that were used to assign non-uniform counts and averages to the counties, and present summary statistics on trends in major water infrastructure, agriculture, and climate characteristics.

Major Water Infrastructure

Our primary source for the major water infrastructure is U.S. Army Corps of Engineers' National Inventory of Dams (NID). The data include information on the location, owner, year of completion, the primary purposes, capacity and height characteristics for major dams in the U.S.[1] The primary purposes of construction include flood control, debris control, fish and wildlife protection, hydroelectric generation, irrigation, navigation, fire protection, recreation, water supply enhancement, and tailings control. Figure 1 shows the major dams in our five-state sample, based on the NID.

As shown in Table 1, approximately 22 percent of the water captured by dams in our five-state sample has irrigation listed as *the* primary purpose and 83 percent of the water has irrigation listed as *a* purpose. Dam construction in the west peaked in the post-WWII period – with the vast majority of dams constructed during the 1950s, 60s and 70s. Over 55 percent of the

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[1] "Major dams" refers to any dams that exceed 25 feet in height with more than 15 acre-feet in total storage; any dams that exceed 6 feet in height with more than 50 acre-feet in storage; or any dams that maintain a "significant" hazard-mitigation classification.

total dam capacity in the Western United States was added during the 1950s and 1960s alone, and over 73 percent was added over that same time-frame in our five-state sample (see Table 2).

Because we are concerned with the impact that dams had on agricultural productivity, correctly connecting the available water supply with agricultural demand is essential. In order to do so, all of the major dams in and around our five-state sample have been spatially merged with the county-level agricultural census data. Therefore, if a county has a major dam located within its boundaries or nearby, it has been assigned access to the supply of dam water (measured in both volume of water and the number of irrigation dams that the county has access) for all subsequent years after dam completion.

Unfortunately, assigning water allocation based solely on the location of the dam itself ignores those counties that are connected to the dam via canals, aqueducts or major river systems. Many major water infrastructure projects are shared by multiple counties and multiple states. In situations where river systems and aqueducts are many hundreds or thousands of miles in length and have multiple dams on the same river, the water supply accordingly is assigned to those counties that are down-stream from the dam, before any subsequent dam. In order to accomplish this adjustment and to create a robustness check for our empirical models, we have contacted and surveyed the operators or management agencies for each of the 475 major dams in our five-state sample. With this survey we are able to determine the actual allocation of water from each dam to the different counties in our study.[2] This survey does not address any temporal

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[2] A questionnaire was administered via telephone to all major dam operators in Idaho, Montana, Wyoming, North Dakota and South Dakota. The information collected through these questionnaires includes whether water is withdrawn onsite, downstream or both, the counties (and the acreages) that dams supply irrigation water, and primary method of withdrawing water (pump or canals).

changes in the supply of water from major dams, but it does provide a more accurate representation of the spatial distribution of water from major dams.[3]

Census of Agriculture Data

Historical agriculture data from the U.S. Census of Agriculture have been collected and inputted manually from hard-copy historical agricultural census records. The data include 20 yearly observations for each county in the sample, assembled between 1900 and 2002. The first few years of the agricultural census were decennial and aligned with the population census, but after 1920 the agricultural census was conducted every 5 years, with a reorganization in 1978 so that the data were collected at two points before the next decennial population census.[4]

From the agricultural census data several different measures of agricultural composition and production have been constructed, including: total planted acreage, total failed acreage, total fallow or idle acreage, and total harvested acreage by crop (measured in tons or bushels per acre). We have collected major crop variables that are found in all five of our sample states, including wheat, barley and hay, as well as major crop variables that are more state/region specific in the west, such as potatoes and corn.

Figures 1 and 2 present the historical trends in agricultural composition and productivity, respectively, in our five sample states. The average trends in agricultural composition presented in Figure 1 indicate that large decreases in hay acreage were experienced throughout the first 25 years of the 20th century, followed by a general decline in average acreage after 1925.

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[3] We were able to collect data on the total number of wells providing water to agriculture in our sample states (see Table 1), but the data is measured in 2009 and therefore doesn't reflect the changing availability of well water over time, nor does it represent the volume of well water available. We acknowledge that the availability of well water and the electrification of the farm increased the agricultural potential of many western counties.

[4] Our yearly observations include 1900, 1910, 1920, 1925, 1930, 1935, 1940, 1945, 1950, 1955, 1960, 1965, 1970, 1975, 1978, 1982, 1987, 1992, 1997, and 2002.

Conversations with research hydrologists justify this decline as a function of hay being a prime input to production for *all* agriculture prior to the mass availability of internal combustion power, but just an input to livestock agriculture after the arrival of heavy planting and harvesting machinery.[5] Wheat acreage increased until the 1950s, and then experienced relatively stagnant growth. What becomes very apparent in Figure 1 is the impact of the mid-1930s dustbowl era droughts – the spikes in failed and idle acreage, and the associated declines in wheat, barley and all of the other major crops.

Figure 2 presents the average trends in agricultural productivity, as measured by output per acre, per crop. All crops experienced increased productivity throughout the 20th century, with relatively larger gains made by corn, barley and wheat. Hay productivity was relatively stagnant, however.

Two issues arise when integrating agricultural data into the analysis: the changing shape of counties over time, and the changing measures or definitions within the agricultural data set. First, because the agricultural census is provided at the county level, and county boundaries have changed over time, we have normalized the agricultural census data to current 2000 census county boundaries. In order to do so, we multiply the historical census count data (measured in acres or volume of output,) by the fraction of the county that lies in the current 2000 census county boundary definition (measured as the percentage of the total land area). In almost all cases the historical county boundaries were subdivided into current boundaries, with very few modifications.[6]

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[5] Personal communication between Scott Lowe and Bryce Contor, research hydrologist with IWRRI -- the University of Idaho Water Resources Research Institute, November 2009.

[6] For example, in Idaho, Alturas County, which existed from 1864 to 1895, was divided over the years into 8 separate counties. The transition to 8 counties was not instantaneous – therefore the number of counties is often different across different Agricultural Census periods. By limiting our period of analysis to the 1900-2002 Agricultural Censuses, we avoid much of the redistricting of county areas that took place in the western United

Second, the crop acreage and harvest data within the census has changed over time. For example, in the early years of the agricultural census, certain forage crops were listed as a single entry, but in later years the forage crops were split into multiple categories. We are limited by the lowest common denominator in these cases. In the models in which we are interested in individual crops that have been further divided into sub-crops, we aggregate so that the unit of measure is consistent across all of the years of our sample.

Climate Data

The U.S. Climate Division Dataset (USCDD) provides averaged climate data based on 344 climatic zones, covering 1895 to present.[7] The USCDD provides temperature and precipitation measures, including the monthly maximum, minimum, mean temperatures and total monthly precipitation levels. In addition, it includes other climate-related variables such as Palmer drought severity indices and standardized z-scores of temperature and precipitation. The Palmer Drought Severity Index (PDSI) is a long-term drought measure that is standardized to the local climate so that it shows relative drought and rainfall conditions in a region at a specific time. It uses temperature and rainfall information in a formula to determine relative wetness or dryness. The Palmer Index is most effective in determining long term drought—a matter of several months. It uses a 0 as normal, with drought periods shown in terms of negative numbers and flood periods shown in terms of positive numbers.[8]

States before the 20th century. Less than 2% of the total observations in our sample were affected by county-level redistricting.

[7] The five-state sample includes 45 distinct climate zones in Idaho (10), Montana (7), North Dakota (9), South Dakota (9), and Wyoming (10).

[8] The Climatic data are from the Area Resource File (ARF). The ARF file is maintained by Quality Resource Systems (QRS) under contract to the Office of Research and Planning, Bureau of Health Professions, within the Health Resources and Services Administration.

The USCDD is zonal in nature: dividing each state into similar climate zones. Unlike monitor-level temperature and precipitation data, the zonal climate data utilize all of the monitor readings within a zone to arrive at zone-averaged temperature and precipitation measures. In addition, there are no missing observations for the zonal climate data, so from year to year the same zones' climate data can be used. Unfortunately, the zones reflect topographic and meteorological uniformities, and therefore don't conform to sociopolitical county boundaries. For this reason, in order to assign zonal climate data to counties that overlap multiple zones, the zonal climate data must be averaged across the overlapping counties.[9]

Topography and Soil Quality Data

We utilize a general topography classification from The National Atlas (USGS), which identifies counties according to their major landform types. The variable we use is the "Land Surface Form Topography code", which identifies 21 different classifications, including plains, tablelands, open hills and mountains. This topography type allows us to group counties according to similar landforms – and the likelihood that they have land that is suitable for growing certain crops. Similarly, the topography type reflects the likelihood that a county has the potential of having a major dam in place: the major western dams are much more likely to occur in the more mountainous counties, or those with open hills, than they are in tablelands or plains.

In addition to landform type, we have collected county-level soil quality (soil type) information from the Natural Resources Conservation Service's (NRCS) Soil Survey Geographic

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[9] We use an evenly weighted average – so if a county falls in two zones, the temperature and precipitation values that are assigned that that county would be 50% of the first zone and 50% of the second zone. As an example, of the 44 counties in Idaho, 28 are contained in a single climate zone, 9 overlap with 2 climate zones, 5 overlap with 3 climate zones, 1 overlaps with 4 climate zones, and 1 overlaps with 5 climate zones. As a robustness check, we will run models with only those counties that are contained in a single climate zone.

(SSURGO) database. The SSURGO database provides a national-coverage of soil quality measures, according to the non-irrigated Land Capability Classification System (LCC). The LCC includes eight classes of land, derived from a series of soil qualities, including percent slope, erosion potential, rooting depth, drainage class, composition, salinity, growing season, average annual precipitation and surface textures. The coverage of each LCC in each county is weighted by total area to arrive at a county-averaged LCC that is time-invariant.

Econometric Model

In this section we describe the econometric strategy used to estimate the impact of major water infrastructure on cropping practices and on crop outcomes (harvest per acre, crop failure, etc.), using the data sources outlined in the previous sections. It is important to note that any empirical exercise that models the impact of water provided by dams on agricultural composition or output may suffer from spurious positive correlation: counties that have the natural amenities present, and thus anticipate a larger productivity gain from an increased volume of irrigation water, may be more likely to invest in a major water infrastructure project. Thus, traditional OLS analyses may be biased. In addition, water supply infrastructure could have brought agricultural production to areas where it was not possible without irrigation, and therefore introduce a potential endogeneity problem. To overcome these issues, we present two different, but related identification strategies.

First, we cluster similar counties based on topographic and climatic types. Identification therefore comes from the within-cluster differences in availability of irrigation water over time. In this case, counties within clusters are very similar in agricultural potential (soil type, annual precipitation total, annual temperature average,) as well as the potential for having a major water

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infrastructure project (topography classification), and we estimate the treatment effect of having irrigation water. To cluster counties, we use a definition of "arability" based on possible profitable production of crops without irrigation on land with low, average and highly variable rainfall, and match counties in our sample accordingly. We then exclude all counties in our sample where profitable agricultural production without irrigation would not be possible. The definition of arability used includes a minimum average rainfall of 10 inches per year; sufficiently deep soil with no clay and sand; and no excessive evaporation due to wind and heat during critical stages of plant growth. We further differentiate the cluster by the topographic characteristics of the county, and therefore control for counties that have similar potential for major water infrastructure.

We let $H_{i,g,t}$ denote the agricultural outcome in county i, in cluster g, in year t. $D_{i,g,t}$ is an indicator variable that equals one when county i has access to irrigation water provided via a major water infrastructure project in year t, and zero otherwise.[10] Our basic econometric model is equation (1) below:

$$H_{i,g,t} = \alpha D_{i,g,t} + \beta I_{i,g,t} + X_{i,g,t}\varphi + Z_{i,g}\mu + \theta_{g,t} + \delta_{g,j} + \eta_{i,g,t} \tag{1}$$

where α is the parameter of interest, and measures the difference in the dependent variable between counties *with and without* major water infrastructure projects.[11] $I_{i,g,t}$ represents the

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[10] We begin with a 50,000 AF cutoff to construct the indicator variable for irrigation water provided by dams, but relax this cutoff as a robustness check. As expected, as the cutoff level decreases, so does the magnitude of the coefficient on the dam indicator variable.

[11] We constrain the major water infrastructure binary variable so that it represents only projects with a dedicated purpose of irrigation. In these cases, dams that were constructed for hydroelectric, recreation or other purposes without any indication that they will provide irrigation water are not included as dams in our analysis of agricultural impacts.

occurrence of a particularly wet or dry period using the PDSI. $X_{i,g,t}$ is a vector of controls that vary over time at the county level, and includes the annual rainfall and temperature measures.[12] $Z_{i,g}$ is a vector of controls that are continuous across time, but vary at the county level. This vector includes the non-irrigated soil capability classification of the county. $\theta_{g,t}$ is a year fixed effect, $\delta_{g,j}$ is a state fixed effect and $\eta_{i,g,t}$ is the unobserved error component.

We allow $H_{i,g,t}$ to represent: 1) percentage measures of agricultural mix (changes in composition), or 2) the successful harvest per acre before and after a major water infrastructure project is completed.[13] To further test whether major water infrastructure provides security during times of drought or flood, we utilize a difference-in-difference model, presented in equation (2) below, where we interact $D_{i,g,t}$ with the indicator variables for those periods in which agriculture experienced droughts and severe floods ($I_{i,g,t}$)[14]:

$$H_{i,t} = \alpha D_{i,g,t} + \beta I_{i,g,t} + \gamma \left[D_{i,g,t} * I_{i,g,t} \right] + X_{i,g,t} \varphi + Z_{i,g} \mu + \theta_{g,t} + \delta_{g,j} + \eta_{i,g,t} \quad (2)$$

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[12] We also include non-linearities in the precipitation and temperature variables in all of our models. As a robustness check, we alter the months that are used to calculate precipitation and temperature totals, including adding the winter (wetter) months in the year prior to the agricultural census, or limiting the climate averages to the summer months during the growing season (to account for dry-cropping or those operations that rely solely on rain and snowfall for crop irrigation). These modifications do not have noticeable effects on our variables of concern.

[13] It is worth noting that in most cases, the dependent variable (be it harvest per acre or the composition (%) of different crops produced,) is not biased by the size of the county. In models in which the total land area of the county may affect results the treatment variable will need to be normalized by the total land area or the size of the county.

[14] We use two cutoffs for to construct the drought and flood dummy variables: with a drought condition represented by PDSI <=-2, and a flood condition represented by PDSI>=2. These cutoffs are considered "moderate to severe droughts/floods" within the PDSI literature. See Palmer (1965) and discussion in the U.S. Department of Commerce, National Oceanic & Atmospheric Administration (2009) website regarding "moderate drought" versus "moderate rainfall" and other categorizations. http://www.drought.noaa.gov/palmer.html

Our second strategy to account for the spurious positive correlation, follows Duflo and Pande (QJE 2007), and takes advantage of the topography classifications of each county as instruments for the likelihood of dam construction. Specifically, we estimate a fixed effects two stage least squares panel regression of the form:

$$D_{i,t} = \left[\tau T_i * \theta_t \right] + \beta I_{i,t} + X_{i,t}\varphi + Z_i\mu + \left[\theta_t * \delta_i \right] + \eta_{i,t} \tag{3}$$

The notation follows from equation (1), with the following exceptions: the topographic classification (T_i) has been interacted with the year fixed effects; the panel fixed effect is now represented by an interaction between the year fixed effect and the state fixed effect to arrive at a state-year fixed effect. To generate instruments for $D_{i,t}$, we utilize the parameter estimates from (3) to predict the likelihood of a dam being constructed ($\hat{D}_{i,t}$) in our first-stage equation. Our final instrumental variables estimation is therefore equation (4):

$$H_{i,t} = \alpha D_{i,t} + \beta I_{i,t} + X_{i,t}\varphi + Z_i\mu + \left[\theta_t * \delta_j \right] + \eta_{i,t} \tag{4}$$

using instruments for $D_{i,t}$ from the parameter estimates from (3).

IV. Results

The objective of this chapter is to examine the impact of major water infrastructure on agricultural composition and productivity. We hypothesize that counties with access to water supply infrastructure are better able to deal with the problems of short-term climatic variability (either due to natural variability in the hydrologic cycle or due to disruptions of the cycle) in

terms of smoothing out agricultural production over time relative to those similar counties without such infrastructure.

It is important to note that the temperature variability and average levels of precipitation are very similar across the five states in our sample, and unlike more temperate western states, the year-to-year water availability is not a significant factor in determining annual crop mix changes. Because of the climate extremes (traditionally represented by very hot summers and very cold winters,) the presence of irrigation water is less essential in our sample states than in states that grow crops that are much more dependent on irrigation water. Many of the crops that we analyze are field crops that can be dry-farmed, unlike row crops that require intensive irrigation to produce any output. For these reasons, we anticipate that the impacts of dam-provided irrigation water are likely to be less significant in states in our sample than in those states that grow crops that are much more dependent on it for their agricultural practices. Thus, we expect that our results likely underestimate the true benefit of the major water infrastructure projects, particularly in those states that have more crop variability, and that are more dependent on dam-provided irrigation water.

Tables 3 through 9 show results from our clustered sample presented in equations (1) and (2) from Section III. Our sample counties are clustered based on similarities in topographic and climatic characteristics; thus, identification in our models comes from the within-cluster differences in availability of irrigation water over time.

Table 3 presents the impact of dams on agricultural composition, shares of total cropland dedicated to certain crops as well as fallow and failed crop acres, controlling for precipitation, temperature, soil quality, and state and year fixed effects, measured within clusters of counties. In our sample counties, annual water variability, and hence, dam-provided irrigation water

availability is not expected to be a significant determinant of crop mix changes. As anticipated, in these models we see that the indicator variable for dams has only a small, insignificant impact on agricultural composition. The indicator variable for droughts, however, which is constructed using PDSI cutoff of "moderate to severe droughts," shows a shift away from wheat and corn during drought periods, and an increase in failed acreage.

When we interact the indicator variables for dams and droughts, in Table 4, we see that the counties that have dams experienced an increase in wheat acreage (+2.46 percent) and a decrease in failed acreage (-4.41 percent) during drought periods relative to those drought areas without dams present.[15]

According to these results, dams had very little impact on the agricultural practices during normal precipitation years, but had a much more significant impact during drought years. Relative to similar counties that did not have dam-provided irrigation water available, counties with the dams were much more successful during difficult growing years—they were able to plant more of their total acreage and they lost less of the crop that was planted.

The results are economically significant. The average aggregate annual wheat acreage across the five states in our sample was 10.2M acres, and the average aggregate annual failed acreage was 1.8M acres. The coefficient on our drought-dam interaction term from Model (2) in Table 4, a 2.46% increase in wheat acreage, is equivalent to an average increase of over 251,000 acres dedicated towards wheat, in aggregate across all states, averaged across all years. Similarly, the coefficient on our drought-dam interaction term from Model (6) in Table 4, a

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[15] We estimated our models using all dams as well as irrigation dams only. Results are qualitatively similar although more significant when we use irrigation dams. We also estimated models showing the impact of dam not only where it is located, but from various distances from dam and again find similar results.

4.41% decrease in failed acreage, is equivalent to an average decrease of approximately 80,000 failed acres, in aggregate across all states, averaged across all years.

Tables 5 and 6 present similar models to Tables 3 and 4, but measure agricultural productivity as opposed to agricultural composition. Agricultural productivity is measured in bushels per acre for wheat, barley and corn; in tonnage per acre for hay and in 100 pounds per acre for potatoes. In these models we see an across-the-board increase in productivity during drought periods, even when total cropland harvested may be declining. For example, we observe a 0.12 ton/acre increase in hay productivity and a 2.96 bushel/acre increase in wheat productivity. Conversations with water resource managers indicate that these results are not all that surprising—when farmers are faced with decreased water availability, they are very careful with their overall water management, thus applying the water that they do have to their most productive acreage. This application practice results in an increased productivity per acre across the fewer acres that are planted.[16]

Similar to Tables 3 and 4, the dam indicator variables have a positive, but insignificant effect on agricultural productivity. This is again due to fact that the presence of irrigation water is likely less essential in our sample states that mostly grow field crops that can be dry-farmed, than in states that grow crops that are much more dependent on irrigation water. When we interact the indicator variables for dams and droughts, in Table 6, we see that the presence of dams in areas that are suffering from droughts has a positive, significant impact on wheat productivity (+3.16 bushels/acre) and barley productivity (+2.61 bushels/acre).

These effects also are economically significant. They are roughly 13 percent and 8 percent, respectively, of the annual mean productivity per acre in our sample. In terms of the

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[16] Personal communication between Scott Lowe and Hal Anderson , Administrator of Planning and Technical Services Division, Idaho Department of Water Resources, November 2009.

total harvest, an increase of 3.16 bushels/acre of wheat translates into an average output increase of approximately 182,000 bushels per county, per year.[17] At the current commodity price for wheat, this is equal to almost a $1M increase in annual revenue, per county (National Agricultural Statistics Service, 2009). To put these results in context, we estimate that the average acres of wheat harvested per county, per year were 57,500 across our study sample. With an average of 23.8 bushels/acre, and an average 2009 commodity price of $5/bushel for wheat, the total revenue per county from wheat is $6.8M per year.

Tables 7 and 8 present similar models to those presented in Tables 5 and 6, but are altered to account for periods of excessive precipitation, as opposed to periods of drought. We want to test for the impact of dams on agricultural productivity during periods of potentially damaging flooding. We use a flood condition represented by PDSI >=2 to create the flood dummy variable indicating "moderate to severe floods / precipitation levels" within the PDSI literature.

Increased levels of precipitation, of course, may have other effects, such as greater opportunity to hold more water behind dams and have water available for even more irrigation to positively impact agricultural productivity of those crops that benefit from extra water availability. On the other hand, increased water availability may also increase the use of marginal land for some crops where output per acre is lower. In addition, damaging levels of precipitation and flooding may decrease overall agricultural productivity levels.

We find that periods of excessive precipitation (shown as the flood indicator variable in the tables) result in a significant positive effect on agricultural productivity of wheat and hay, the two dry-farmed crops in our sample. These results are presented in Models 1 and 2 on Table 7.

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[17] The mean harvest, measured at the county level between 1900 and 2002, was 57,500 acres of wheat, 41,700 acres of hay, 12,400 acres of barley, 3,300 acres of corn, and 1,370 acres of potatoes. These numbers are larger (with the exception of hay) for the latter half of the 20th century than the first half, but had more variation across counties in the latter years.

Extra water storage and the availability of more water for irrigation to be applied to lands that are typically cultivated by using dry-cropping techniques is the likely explanation for the positive and significant effect on the total productivity of wheat and hay, ceteris paribus.

The general precipitation variable for wheat has a negative effect for wheat productivity. This result, combined with agricultural composition results presented in Tables 3 and 4 that show that share of total cropland in wheat declines when there is increased precipitation. This result indicates that some of the most productive lands are shifted away from wheat production during wet seasons to alternative crops, especially more water-intensive potatoes.

Although the presence of a dam alone has a limited impact on agricultural productivity in our sample states, when this effect is interacted with the presence of a period of excessive precipitation (and increased likelihood of flooding), we find a positive impact for all agricultural productivities studied. Results, shown in Table 8, indicate that the productivity of wheat (+2.14 bushels/acre) and corn (+4.52 bushels/acre) are statistically significant and positive. These effects are roughly 9 percent and 13 percent of the annual mean productivity per acre in our sample. The overall increased productivity impact of dams during periods of excessive precipitation may be due to the prevention of damaging flooding when a dam is present, plus the availability of greater irrigation water held behind dams.

Table 9 presents the results of the empirical models outlined in Model (4) of Section III. In these models, we use a two-staged fixed effects process, following Duflo and Pande (2007), in which we instrument for the likelihood of a county having a dam, using topographic characteristics of counties (interacted with year effects) in addition to all of the independent variables that we use to explain the variation in crop composition and productivity. This is another econometric strategy we implement to address the likely spurious positive correlation

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and endogeneity problems we face in our econometric identification: those counties that have the natural characteristics for dam presence, and thus anticipate a larger productivity gain from dams, are also more likely to invest in a major water infrastructure project.

The results of instrumental variable approach, presented in Table 9, are in general consistent with our previous results. However, unlike our findings in Tables 3 through 8, the fixed effects instrumental variables results suggest that the presence of a dam has a large, positive impact on all crops, and a significant impact on hay productivity (+0.94 tons/acre), wheat productivity (+7.1 bushels/acre), and barley productivity (+22.90 bushels/acre). [18] We also continue to find positive impacts of droughts on productivity, but these effects are only marginally significant.[19]

All told, our results from the various estimation strategies indicate that the availability of water infrastructure increases agricultural productivity and the likelihood of successful harvest as measured by harvested cropland as a share of total cropland. Although dams, in our sample, may have had little impact on agricultural composition and agricultural productivity during *normal* precipitation years, when we interact the indicator variables for dams and droughts, however, we find that the counties that have dams experienced an increase in wheat acreage (+2.46 percent) and a decrease in failed acreage (-4.41 percent). Relative to similar counties that did not have

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[18] Given our concern with spurious positive correlation, we had expected to find reduced magnitude in the estimated coefficients and possibly improved standard errors when we use a two-staged fixed effects process. We instead find increased coefficient estimates. This may be due to the weakness of our main instrument for dams: topography of counties. For broader work on this topic, we are exploring alternative instruments, such as river gradient, details on reservoir site (wide or narrow valley), county elevation and length of rivers.

[19] As noted earlier, we were able to collect data on the total number of wells providing water to agriculture in our sample states, but the data is measured in 2009 and therefore doesn't reflect the changing availability of well water over time, nor does it represent the volume of well water available. As a robustness check, we introduce the well availability as both a time invariant indicator variable and as a dummy variable (which is in turn instrumented for endogeneity) for all years after 1950, when most western farms uniformly had access to electricity. The inclusion of these well variables slightly reduces the magnitudes of our variables of concern, but doesn't alter their significance, signs or their general magnitudes.

dam-provided irrigation water, counties with the dams were able to have more of their total acreage planted and lost less of the crop that was planted. Similarly, the results presented in Table 6 show that the presence of dams in areas that are suffering from droughts has a positive, significant impact on wheat productivity (+3.16 bushels/acre) and barley productivity (+2.61 bushels/acre).

In addition, our results also indicate that the presence of major water infrastructure helped to mitigate the damages of periodic floods. As shown in Tables 7 and 8, periods of excessive precipitation result in a significant positive effect on agricultural productivity of wheat and hay, the two dry-farmed crops in our sample. Again, the presence of a dam alone only has a limited impact on agricultural productivity, but when this effect is interacted with the presence of a period of excessive precipitation, we find a positive impact for all agricultural productivities studied. Results presented in Table 8 indicate that the increased productivity of wheat (+2.14 bushels/acre) and corn (+4.52 bushels/acre) are statistically significant and positive.

V. Summary and Conclusions

Climate change is a major issue and much of the scientific focus is on its likely impact and the costs of various paths of mitigation. Less attention has been directed towards adaption— of how policies and markets have addressed past climate shocks. This is vital information because adaptation to climate change can influence both its effects and the costs of addressing it. The empirical evidence on past adaptation policies is limited. This chapter examines the impact of one of the most extensive water infrastructure investments ever made—the "reclamation" systems of the U.S. West— to determine their impact on agricultural production in the face of severe drought or flooding. Water infrastructure is particularly important as a long-term adaptation strategy to climate change because dams and associated canals are among the longest-

lasting infrastructures in agriculture, and investment in them differs from most other agricultural adaptation strategies available to farmers (Reilly, 1999).

Analysis of historical data from the western U.S., where temperature and precipitation differences relative to the eastern part of the country are greater than those predicted from climate change models, allows for assessment of adaption policies. We present a large-scale time series analysis of historical data on mitigation of the impact of climate change on agricultural production. Because there is evidence that mean changes in temperature may have less impact on agricultural production, our focus is on extremes of precipitation levels that are likely to cause significant negative agricultural outcomes. This approach follows the recommendation of Reilly (1999) and others regarding analysis of the impact of climate change on agricultural production. Our results indicate that historical water supply investments have increased agricultural productivity and improved the likelihood of successful harvest during times of climatic shocks—droughts and floods. These are characteristic of the semi-arid west and may become more so if climate projections of greater swings in drought and flooding come to pass.

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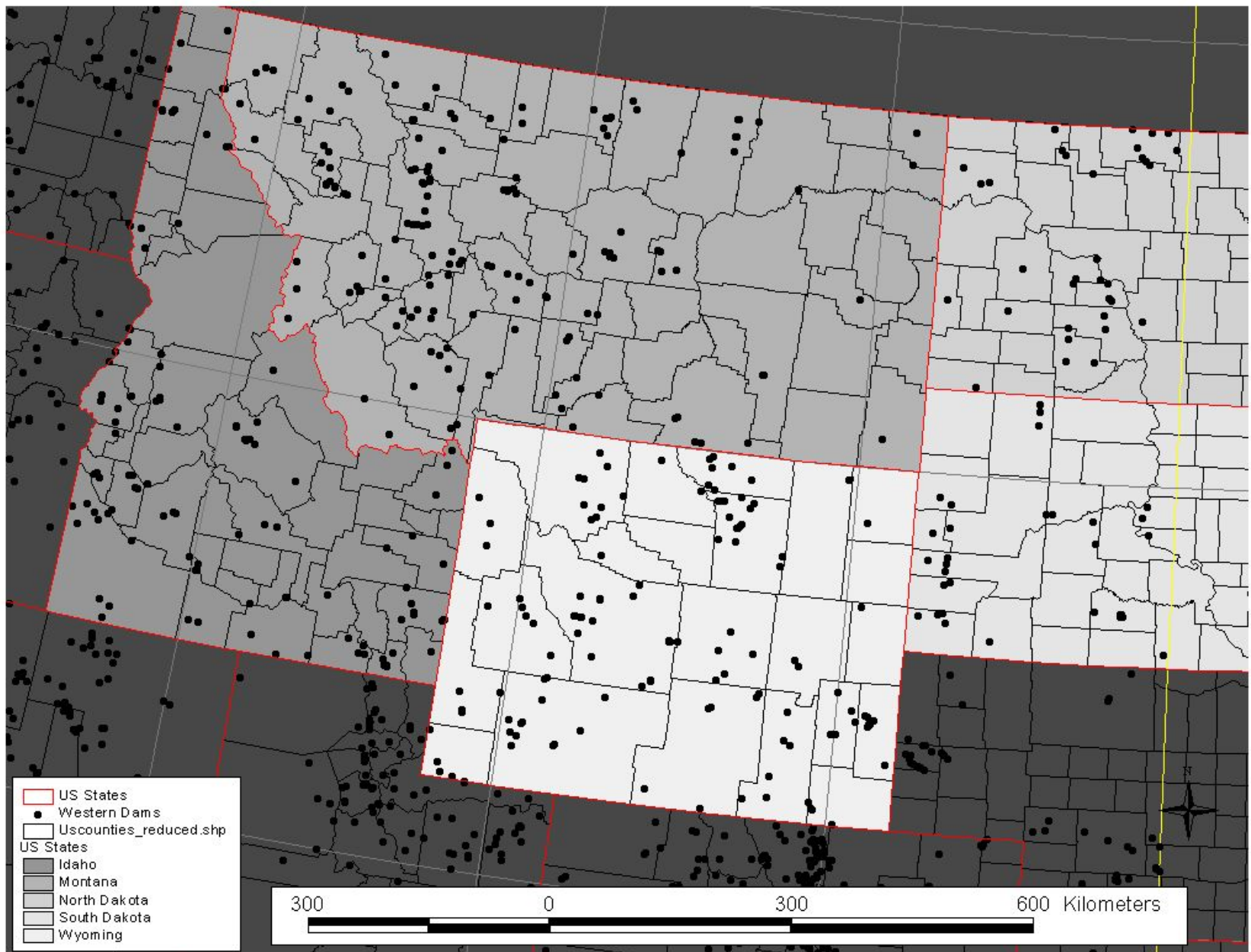
Map 1: Sample Location with State, Counties, and Major Dams West of the 100th Meridian

Table 1: Primary Purpose of Water Provided by Dams (total maximum-storage measured in Acre-feet)

State:	ID	MT	ND	SD	WY
Flood Control	3,947,643	19,130,823	25,208,840	23,618,835	4,589,966
HydroElectric	5,870,818	10,913,527			758,390
Irrigation	7,146,890	10,569,892	500,860	1,692,602	7,486,167
Recreation	5,500	15,430	51,762	31,443	
Water Supply	235,583	107,467		439,758	433,015
Other	384,290	97,176	21,256	100,970	361,721
Total:	17,590,724	40,834,315	25,782,719	25,883,608	13,629,259
# Wells in 2009	31,400	4,220	860	2,680	1,740
"Irrigation" listed as a purpose	8,483,473	31,186,090	25,000,860	25,736,800	12,691,233

Note: "Other" includes Debris Control, Fish and Wildlife, Fire Protection, Tailings and Other
"Total" is different from Table 2 due to ommitted primary purpose for dam

Table 2: Storage and Count of Dams

State:	ID		MT		ND		SD		WY	
Year Completed	Storage	#	Storage	#	Storage	#	Storage	#	Storage	#
<1910	1,604,365	13	324,453	7	0	0	0	0	2,895,107	12
1910-1919	2,173,450	14	1,523,704	24	2,068	1	186,837	2	2,760,933	5
1920-1929	131,573	6	691,403	17	0	0	0	0	257,250	11
1930-1939	303,378	6	2,953,150	36	529,358	11	25,353	3	1,290,735	12
1940-1949	1,169,090	10	415,850	15	500,860	3	116,794	4	94,494	3
1950-1959	5,874,917	10	26,625,161	28	24,505,318	2	1,835,649	7	4,742,634	21
1960-1969	64,459	8	2,133,834	15	53,163	6	23,617,135	4	749,376	20
1970-1979	5,500,870	15	6,129,722	14	189,464	8	5,690	10	387,056	19
1980-1989	134,287	11	8,929	3	2,206	2	5,250	2	336,585	20
1990-2000	255,707	8	24,450	1	0	0	20,900	1	115,089	11
Unknown	378,628	10	3,659	2	282	1	70,000	1	0	0
Total:	17,590,724	111	40,834,315	162	25,782,719	34	25,883,608	34	13,629,259	134

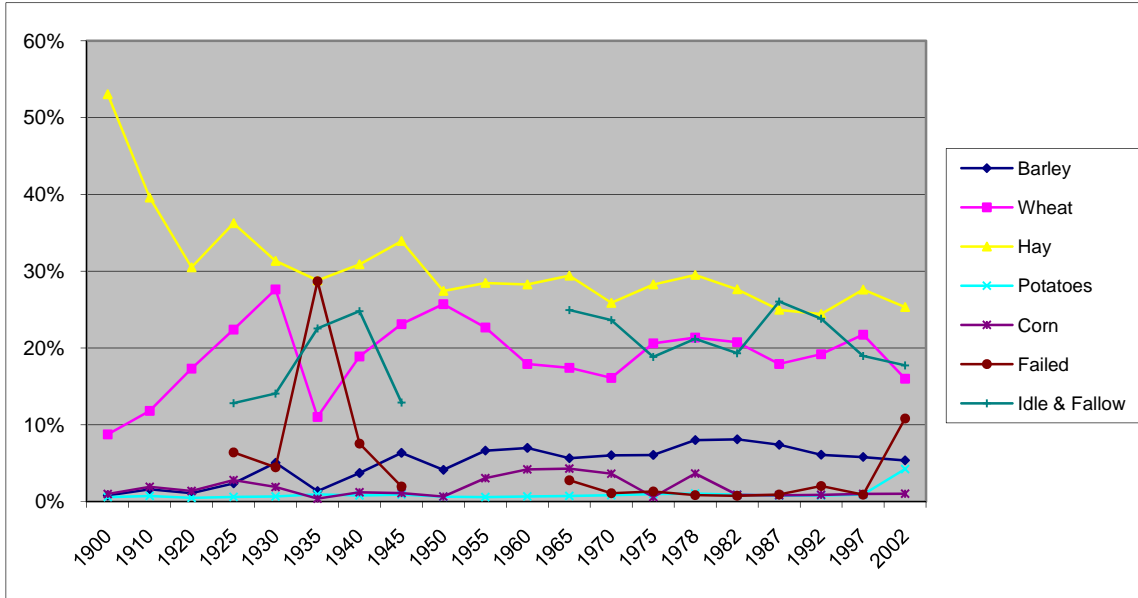Note: Storeage reflects the maximum storage, in AF, behind the dams in the given state

Figure 1: Historical Agricultural Composition, % of total acreage
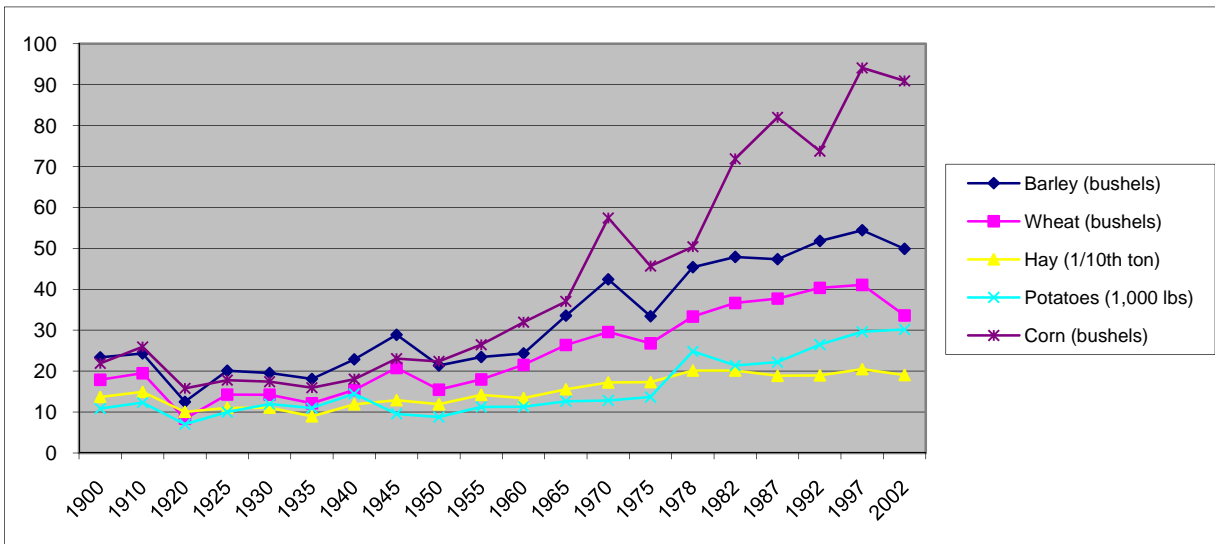

Figure 2: Historical Agricultural Productivity, average per acre

Table 3: Fixed Effects Models of Agricultural Composition With Geograhic-Climate Clusters

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Var:	% Hay	% Wheat	% Barley	% Corn	% Potatoes	% Failed	% Fallow
Dam Dummy	0.0038	-0.0018	0.0047	-0.0113	0.0009	-0.0035	0.0142
	(0.0305)	(0.0197)	(0.0066)	(0.0055)*	(0.0022)	(0.0050)	(0.0190)
Precipitation	0.1494	-0.1671	0.0345	-0.0081	0.0005	0.1673	0.0676
	(0.1024)	(0.0612)**	(0.0226)	(0.0290)	(0.0051)	(0.0705)**	(0.0722)
Precipitation Squared	-0.0406	0.0316	-0.0159	0.0004	-0.0031	-0.0394	-0.0150
	(0.0291)	(0.0220)	(0.0064)**	(0.0090)	(0.0010)***	(0.0217)*	(0.0201)
Temperature	-0.0417	0.0258	-0.0045	-0.0055	0.0161	0.0064	0.0351
	(0.0503)	(0.0299)	(0.0201)	(0.0095)	(0.0066)**	(0.0189)	(0.0233)
Temperature Squared	0.0004	-0.0003	0.0000	0.0001	-0.0002	-0.0000	-0.0004
	(0.0006)	(0.0003)	(0.0002)	(0.0001)	(0.0001)**	(0.0002)	(0.0003)
Soil type	0.0412	-0.0317	-0.0014	-0.0029	-0.0023	-0.0010	-0.0194
	(0.0221)*	(0.0067)***	(0.0031)	(0.0042)	(0.0020)	(0.0022)	(0.0145)
Drought Dummy	0.0281	-0.0500	0.0032	-0.0070	0.0025	0.0215	-0.0368
	(0.0199)	(0.0085)***	(0.0054)	(0.0036)*	(0.0012)*	(0.0066)***	(0.0120)***
Observations	3498	3482	3471	3372	3359	2415	2407
Geographic-Climate Clusters	16	16	16	16	16	16	16
R-squared	0.18	0.20	0.27	0.16	0.25	0.52	0.29
Year FEs	YES	YES	YES	YES	YES	YES	YES
State FEs	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 4: Difference-in-Difference Fixed Effects Models of Agricultural Composition With Geograhic-Climate Clusters

Model:	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Dep Var:	% Hay	% Wheat	% Barley	% Corn	% Potatoes	% Failed	% Fallow
Dam Dummy	0.0004	-0.0071	0.0059	-0.0136	0.0006	0.0055	0.0157
	(0.0325)	(0.0208)	(0.0055)	(0.0062)**	(0.0018)	(0.0044)	(0.0191)
Precipitation	0.1523	-0.1627	0.0335	-0.0060	0.0007	0.1584	0.0663
	(0.1028)	(0.0621)**	(0.0235)	(0.0290)	(0.0049)	(0.0724)**	(0.0735)
Precipitation Squared	-0.0416	0.0300	-0.0156	-0.0003	-0.0032	-0.0361	-0.0145
	(0.0293)	(0.0223)	(0.0067)**	(0.0091)	(0.0010)***	(0.0221)	(0.0204)
Temperature	-0.0421	0.0252	-0.0043	-0.0057	0.0160	0.0076	0.0354
	(0.0500)	(0.0300)	(0.0199)	(0.0094)	(0.0066)**	(0.0180)	(0.0237)
Temperature Squared	0.0004	-0.0003	0.0000	0.0001	-0.0002	-0.0000	-0.0005
	(0.0006)	(0.0003)	(0.0002)	(0.0001)	(0.0001)**	(0.0002)	(0.0003)
Soil type	0.0412	-0.0318	-0.0014	-0.0029	-0.0023	-0.0010	-0.0194
	(0.0220)*	(0.0068)***	(0.0031)	(0.0042)	(0.0020)	(0.0023)	(0.0145)
Drought Dummy	0.0247	-0.0553	0.0044	-0.0093	0.0022	0.0310	-0.0352
	(0.0209)	(0.0102)***	(0.0048)	(0.0050)*	(0.0016)	(0.0057)***	(0.0112)***
Drought-Dam Interaction	0.0159	0.0246	-0.0056	0.0110	0.0015	-0.0441	-0.0074
	(0.0248)	(0.0120)*	(0.0111)	(0.0064)	(0.0022)	(0.0079)***	(0.0174)
Observations	3498	3482	3471	3372	3359	2415	2407
Geographic-Climate Clusters	16	16	16	16	16	16	16
R-squared	0.18	0.20	0.27	0.16	0.25	0.53	0.29
Year FEs	YES	YES	YES	YES	YES	YES	YES
State FEs	YES	YES	YES	YES	YES	YES	YES

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 5: Fixed Effects Models of Agricultural Productivity With Geograhic-Climate Clusters

Dep. Var: (Output / acre)	(1) Prod Hay	(2) Prod Wheat	(3) Prod Barley	(4) Prod Corn	(5) Prod Potatoes
Dam Dummy	0.0123	0.3328	0.5809	2.9639	7.2172
	(0.0480)	(0.8814)	(0.8567)	(1.9674)	(6.1585)
Precipitation	0.3182	-6.1633	4.4790	15.0053	93.7036
	(0.2458)	(4.2880)	(3.9326)	(11.0013)	(32.5217)**
Precipitation Squared	-0.1098	0.9087	-2.1465	-8.0377	-29.3468
	(0.0732)	(1.0289)	(0.9230)**	(3.2000)**	(7.5700)***
Temperature	0.0603	-2.3920	-0.4798	0.5813	-4.0923
	(0.2465)	(3.1610)	(3.8940)	(5.6545)	(21.9671)
Temperature Squared	-0.0004	0.0299	0.0059	0.0018	0.0632
	(0.0029)	(0.0374)	(0.0439)	(0.0634)	(0.2528)
Soil type	0.0338	1.0415	1.3763	0.5997	2.7186
	(0.0480)	(0.6582)	(0.7562)*	(0.8414)	(3.4159)
Drought Dummy	0.1209	2.9577	2.8479	7.6389	27.5879
	(0.0505)**	(0.8035)***	(0.6823)***	(1.1996)***	(11.3440)**
Observations	3506	3420	3413	2328	2634
Geographic-Climate Clusters	16	16	16	16	16
R-squared	0.53	0.60	0.66	0.71	0.20
Year FEs	YES	YES	YES	YES	YES
State FEs	YES	YES	YES	YES	YES

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 6: Difference-in-Difference Fixed Effects Models of Agricultural Productivity With Geograhic-Climate Clusters

Dep. Var: (Output / acre)	(1) Prod Hay	(2) Prod Wheat	(3) Prod Barley	(4) Prod Corn	(5) Prod Potatoes
Dam Dummy	-0.0067	-0.4286	0.0188	2.8026	3.0916
	(0.0415)	(0.9418)	(0.7529)	(1.9337)	(7.8396)
Precipitation	0.3350	-5.7519	4.8524	15.1235	96.1183
	(0.2388)	(4.2002)	(3.9769)	(10.8108)	(32.4707)***
Precipitation Squared	-0.1158	0.7523	-2.2842	-8.0737	-30.1155
	(0.0711)	(1.0107)	(0.9418)**	(3.1360)**	(7.7400)***
Temperature	0.0583	-2.5230	-0.5571	0.5670	-5.0299
	(0.2467)	(3.1334)	(3.9098)	(5.6679)	(22.2777)
Temperature Squared	-0.0004	0.0314	0.0068	0.0019	0.0737
	(0.0029)	(0.0370)	(0.0440)	(0.0635)	(0.2555)
Soil type	0.0338	1.0307	1.3675	0.5965	2.6699
	(0.0481)	(0.6582)	(0.7552)*	(0.8421)	(3.4237)
Drought Dummy	0.1013	2.1855	2.2760	7.4923	24.1668
	(0.0533)*	(0.7126)***	(0.7209)***	(1.3703)***	(12.1120)*
Drought-Dam Interaction	0.0903	3.6065	2.6113	0.7814	17.8331
	(0.0528)	(1.1923)***	(1.2537)*	(2.3636)	(17.7115)
Observations	3506	3420	3413	2328	2634
Geographic-Climate Clusters	16	16	16	16	16
R-squared	0.53	0.60	0.66	0.71	0.21
Year FEs	YES	YES	YES	YES	YES
State FEs	YES	YES	YES	YES	YES

Robust standard errors in parentheses
* significant at 10%; ** significant at 5%; *** significant at 1%

Table 7: Fixed Effects Models of Agricultural Productivity With Geograhic-Climate Clusters

Dep. Var: (Output / acre)	(1) Prod Hay	(2) Prod Wheat	(3) Prod Barley	(4) Prod Corn	(5) Prod Potatoes
Dam Dummy	0.0126	0.3072	0.5481	3.2722	7.0380
	(0.0506)	(0.8782)	(0.8637)	(2.1265)	(6.5410)
Precipitation	0.0268	-13.0083	-0.3792	0.7309	57.3807
	(0.2082)	(4.6598)**	(4.1653)	(10.7330)	(26.8012)**
Precipitation Squared	-0.0580	2.1824	-1.1781	-4.8988	-21.8682
	(0.0660)	(1.1178)*	(0.9004)	(3.0446)	(6.3280)***
Temperature	0.0617	-2.3434	-0.6577	0.2194	-5.5828
	(0.2533)	(3.2984)	(3.9774)	(5.5347)	(21.9204)
Temperature Squared	-0.0004	0.0298	0.0081	0.0075	0.0816
	(0.0030)	(0.0390)	(0.0449)	(0.0620)	(0.2531)
Soil type	0.0389	1.1521	1.4650	0.7392	3.4508
	(0.0484)	(0.6787)	(0.7816)*	(0.8652)	(3.4181)
Flood Dummy	0.1398	2.9364	0.8852	1.9395	-1.1331
	(0.0347)***	(0.7315)***	(0.8744)	(1.5675)	(8.0507)
Observations	3506	3420	3413	2328	2634
Geographic-Climate Clusters	16	16	16	16	16
R-squared	0.54	0.60	0.66	0.70	0.20
Year FEs	YES	YES	YES	YES	YES
State FEs	YES	YES	YES	YES	YES

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 8: Difference-in-Difference Fixed Effects Models of Agricultural Productivity With Geograhic-Climate Clusters

Dep. Var: (Output / acre)	(1) Prod Hay	(2) Prod Wheat	(3) Prod Barley	(4) Prod Corn	(5) Prod Potatoes
Dam Dummy	-0.0021	-0.2770	0.1311	2.2655	4.1813
	(0.0493)	(0.8708)	(1.0194)	(2.0239)	(6.5446)
Precipitation	0.0182	-13.2862	-0.6033	0.4775	56.1630
	(0.2100)	(4.7839)**	(4.3083)	(10.9863)	(26.8280)*
Precipitation Squared	-0.0550	2.2842	-1.0985	-4.7831	-21.4047
	(0.0667)	(1.1547)*	(0.9332)	(3.1454)	(6.3653)***
Temperature	0.0639	-2.2708	-0.5916	0.2069	-5.2821
	(0.2528)	(3.3171)	(3.9742)	(5.5170)	(22.0397)
Temperature Squared	-0.0004	0.0290	0.0073	0.0075	0.0778
	(0.0030)	(0.0392)	(0.0448)	(0.0618)	(0.2547)
Soil type	0.0387	1.1438	1.4576	0.7302	3.3650
	(0.0485)	(0.6806)	(0.7816)*	(0.8739)	(3.4402)
Flood Dummy	0.1267	2.4195	0.5073	1.1066	-4.0288
	(0.0361)***	(0.6928)***	(0.7736)	(1.4970)	(8.7669)
Flood-Dam Interaction	0.0535	2.1364	1.5742	4.5210	12.1472
	(0.0316)	(0.9720)**	(1.3151)	(2.1746)*	(8.5258)
Observations	3506	3420	3413	2328	2634
Geographic-Climate Clusters	16	16	16	16	16
R-squared	0.54	0.60	0.66	0.70	0.20
Year FEs	YES	YES	YES	YES	YES
State FEs	YES	YES	YES	YES	YES

Robust standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Table 9: Fixed Effects Two Stage Least Squares Models of Agricultural Productivity

Dep. Var: (Output / acre)	(1) Prod Hay	(2) Prod Wheat	(3) Prod Barley	(4) Prod Corn	(5) Prod Potatoes
Dam Dummy	0.9449	7.0894	22.9035	7.5803	16.8781
	(0.2260)***	(3.1919)**	(4.8980)***	(8.6688)	(50.1415)
Precipitation	-0.6948	-16.2502	-11.3826	-2.5440	88.4890
	(0.1792)***	(2.7630)***	(3.9622)***	(6.7786)	(38.4334)**
Precipitation Squared	0.0553	4.8924	3.2137	0.0489	-37.1447
	(0.0594)	(0.9126)***	(1.3135)**	(2.2179)	(12.9879)***
Temperature	-0.0478	-8.8767	0.4770	-4.8688	-34.8418
	(0.1217)	(1.6791)***	(2.7007)	(3.1910)	(21.6511)
Temperature Squared	0.0012	0.1092	0.0020	0.0617	0.4318
	(0.0014)	(0.0187)***	(0.0300)	(0.0351)*	(0.2429)*
Drought Dummy	0.0684	0.6081	0.7513	0.0979	25.9228
	(0.0388)*	(0.5750)	(0.8448)	(1.2899)	(7.6828)***
Observations	3506	3420	3413	2328	2634
State-Year FEs	YES	YES	YES	YES	YES

Standard errors in parentheses

* significant at 10%; ** significant at 5%; *** significant at 1%

Instrument: Topography-Year Interaction Variable