Adversity and the Propensity to Fail:
The Impact of Disaster Payments and Multiple Peril Crop Insurance on U.S. Farm Exit Rates

Barrett Kirwan*

University of Illinois at Urbana-Champaign

ABSTRACT

This paper investigates the effect of government-provided crop insurance on farm failure rates. By exploiting random variation in weather and the Federal Crop Insurance Reform Act of 1994, which mandated crop insurance coverage for the first time, I employ two natural experiments that identify the causal effect of disaster relief on farm failure rates. I examine the survival smoothing contribution of crop insurance by looking at the relative effect of disaster relief across two regimes, pre- and post-1994. Prior to 1994 *ad hoc*, *ex post* disaster payments were the primary form of disaster relief. Shortly after the 1994 Act virtually all disaster relief came through crop insurance indemnities. I find that disaster relief in the form of *ad hoc* disaster payments reduces the average farm failure rate, while average farm failure rates increase under the crop insurance regime. The relative effect suggests that farm failure rates increase by 1.7 percentage points (about 30-percent) under the crop insurance regime. Excessively generous *ad hoc* disaster payments and moral hazard provide possible explanations for these findings. These findings suggest that government-provided crop insurance plays an important role in farmer risk management.

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Contact: bkirwan@illinois.edu

1 Introduction

> *"Crop insurance and a system of storage reserves would help to protect the income of individual farmers against the hazards of crop failure; it would help to protect consumers against shortages of food supply and against extremes of prices; and finally, it would assist in providing a more nearly even flow of farm supplies, thus stabilizing farm buying power and contributing to the security of business and employment."*
>
> \- Franklin D. Roosevelt, February 18, 1937

A key purpose of government-provided insurance is to help recipients smooth income or consumption during adversity. The marginal contribution of government-provided insurance, however, may be small when there are many other means of risk management. Farmers in particular have a myriad of risk management devices such as self-insurance through savings, crop diversification, and many financial instruments and contract types, to name a few. Although much research has examined adverse selection and moral hazard in crop insurance markets, few have addressed the income smoothing and business security benefits of this program. As policy makers seek the optimal size, scope, and program design, they require information on both the costs and the benefits of crop insurance, as well as the effectiveness of various crop insurance designs. Recent legislation focused on crop insurance demonstrates the salience of this information.

Weather events have always played a significant role in the decline in the number of farms in the U.S. Spurred by the 1862 Homestead Act, the number of farms in the U.S. grew rapidly from 2 million in 1862 to 6.5 million in 1917. From 1917-1921 farmers in the newly settled Midwest and Great Plains experienced their first major drought, which slowed the growth in the number of farms. As demonstrated in figure 2, the number of farms in the U.S. peaked in 1935 and declined precipitously until the last decade when numbers have leveled off at about 2 million farms.[1] As vividly captured in Steinbeck's *Grapes of Wrath*, the decade long drought that caused the Dust Bowl in the 1930s contributed greatly to the initial decline in farms in the late 1930s. More recently, major weather events such as the 1988 drought in the Midwest, the 1993 flooding in the Midwest, and the 2012 Midwestern drought have captured media attention and galvanized support for the family farmer.

The popular perspective on the declining number of farms overlooks the economic efficiency brought about through farm failure. Economists since Hayek and Schumpeter have recognized the economic benefits of reallocating productive resources from inefficient firms to efficient firms. The near century-long decline in farm numbers is due in no small part to rapid technological advancement and shifting factor prices (Barkley 1990; Huffman and Evenson

[1] Since 1974, the definition of a farm has been based on $1,000 worth of agricultural production, a nominal amount whose real value has eroded thereby liberalizing the definition of a farm and contributing to the apparent leveling off of farm numbers.

2001). Thus, from an efficiency standpoint the declining number of farms is not particularly disconcerting, but the relative increase in the decline due to temporary shocks, such as weather shocks, may be a source of concern. Credit market imperfections may prevent viable firms from smoothing temporary shocks, resulting in inefficient failures due to adverse shocks.

An important element of perfect credit markets is the existence of state-contingent contracts, e.g. insurance. For instance, in the presence of liquidity constraints efficient firms benefit from the ability to insure against temporary adverse shocks (Kiyotaki and Moore 1999; Krishnamurthy 2003). The absence of insurance contracts, for instance due to asymmetric information, may be a market imperfection leading to inefficient farm turnover. In this case, government-provided insurance increases efficiency by overcoming the market failure and allowing viable farms to smooth temporary shocks.

Insurance market failures due to adverse selection provide the key motive for government intervention. The government addresses these insurance market failures in a number of different ways. Typically, the government mandates that all individuals or all firms participate in an insurance market and pay premiums through specific taxes (e.g. Social Security for individuals and unemployment insurance for firms) or through premiums to private insurers (e.g. workers compensation). However, in the case of multiple peril crop insurance (MPCI), the government tries to entice farmers by generously subsidizing the insurance premiums paid by individuals to private insurers that are subsequently reinsured by the government. Due to low participation (about 25-percent of eligible acres in the 80s and early 90s) adverse selection continued to be a significant problem (Just et al., 1999; see Goodwin and Smith, 1995, for a comprehensive review of early studies).

Moral hazard comprises another cost that influences the design of government-provided insurance programs. In the crop insurance literature investigators have focused on two moral hazard-induced types of behavior: input use and cropland choice. Several researchers examined input use, such as fertilizers and chemicals, and found that input use is negatively correlated with crop insurance (Quiggen et al., 1993; Babcock and Hennessy, 1996; Goodwin and Smith, 2003). Others have investigated the influence of crop insurance on the type and amount of land in production (Claasen et al., 2005; Wu, 1999; Goodwin et al., 2004). This body of work has generally found that crop insurance is associated with more environmentally sensitive land being brought into production.

In contrast to the voluminous work examining the costs associated with crop insurance, little has been done to investigate the benefits. This paper fills that gap. By exploiting random variation in weather and a major policy change in 1994, I exploit two natural experiments that identify the causal effect of crop insurance on farm failure rates. My empirical design also allows me to address crop insurance program design issues by comparing the effectiveness of crop insurance versus *ad hoc*, *ex post* disaster payments. Making this comparison also gives insight into the crop insurance induced crowd-out of other risk management behaviors.

In the analysis I focus on two regimes, one primarily consisting of *ex post* disaster payments in 1994 and the other a purely crop insurance regime in 1995. I find that during the disaster payments regime farms experiencing a disaster are less likely to fail than farms that are not hit by disaster, while under the crop insurance regime I find that disaster-stricken farms are about 1.3 percentage points more likely to fail. The lower failure rate under the disaster payment regime does not necessarily indicate that it is more efficient. In light of the 'efficient failure' argument above, the lower failure rate more likely speaks to the inefficient allocation of funds under the politically driven disaster payments regime. Garrett et al. (2006) provide evidence that key political figures allocate relatively more disaster payments to their constituents. Hence the lower failure rate may indicate that inefficient farms are being artificially propped up.

Although the absolute effects of crop insurance are immeasurable without a base period free from government provided assistance, I compare the two regimes to find that farms are about 2 percentage points (30-percent) more likely to fail under mandatory crop insurance than under a program primarily consisting of *ex post* disaster payments. Moral hazard associated with *ex ante* crop insurance provides a plausible explanation of the increased failure rate. Future research with more appropriate data will test this hypothesis.

Although somewhat surprising, the relative effect supports the idea that government provided crop-loss assistance does not completely crowd out other means of risk management. If farmers were able to fully insure through some other means, variation in crop insurance regimes would not alter failure rates. The 30-percent relative effect suggests that government intervention can potentially play a significant role in this market.

The rest of the paper is structured as follows. Section 2 lays out the policy and program background. Section 3 introduces the empirical strategy. The data are discussed in section 4. Section 5 presents the empirical results. The interpretation and conclusion are put forward in section 6.

2 Background

Passed as part of New Deal legislation, the Agricultural Adjustment Act of 1938 introduced the Federal Crop Insurance Program as a form of social insurance meant to smooth the consumption of the 32 million people living on farms in the United States. Spurred on by the decade-long drought that produced the Dust Bowl, policy makers established a national crop insurance product for wheat that insured against losses due to, "drought, flood, hail, wind, winterkill, lightning, tornado, insect infestation, plant disease, and … other unavoidable causes…" (52 *Stat*. 74). Private firms had previously tried and failed to provide multiple peril crop insurance (MPCI). Owing to the geographic concentration of their policyholders, private insurance firms succumbed to geographically correlated weather events, such as drought and flooding. Private insurance companies succeeded only in providing insurance for hail and fire, events that are typically spatially uncorrelated.

Due to poor farm-level yield data, as well as problems with the program design, the Federal Crop Insurance Corporation (FCIC), a U.S. Department of Agriculture agency established to manage the Federal Crop Insurance Program, failed to take in more in premiums than it paid out in indemnities for the first 8 years of operation. In spite of this, while the FCIC made adjustments to the program, MPCI was extended to cotton in 1942 and flax in 1945. In 1947 crop insurance premiums finally exceeded indemnity payments. However, in that same year Congress severely reduced the program size, essentially making it an experimental program. From 1947 until 1981 the Federal Crop Insurance Program remained a relatively small experimental program; by 1980 only about half of the counties in the U.S. and just 26 crops were eligible for insurance coverage.

While crop insurance was in an experimental phase, Congress pursued another method to address the crop insurance market failure. The Agriculture and Consumer Protection Act of 1973 and the Rice Production Act of 1975 established a disaster payments program, which, for some crops, overlapped with the protection provided by federal crop insurance. Essentially, disaster payments amounted to free universal coverage for a select group of crops.[2] Low-yield payments were made to farmers who participated in income- and price-support programs when yields fell below two-thirds of normal. This program was popular with farmers because it provided catastrophic coverage with no premium. However, detractors claimed that the program resulted in heavily distorted behavior. In particular, they argued that the moral hazard behavior of farmers planting on high-risk, environmentally sensitive land imposed a great cost to society. As a result, the program ended in 1981, having paid out $3.4 billion in total.

The modern era of federal crop insurance began with passage of the Federal Crop Insurance Act of 1980. The Act authorized crop insurance expansion to every county in the United States with significant agriculture and to every crop with sufficient actuarial data to establish premiums. In 1981, 252 additional counties received crop insurance, resulting in 1,340 additional county programs (a county program is a particular crop-county combination). Crop insurance extended to 1,050 additional counties in 1982, adding 8,278 county programs.

Crop insurance policies were consistently structured from 1980 – 1994. Producers selected from three guaranteed yield levels (50-, 65-, or 75-percent of their insurable yield) and from three guaranteed price levels. Price election levels were determined from FCIC forecasts of expected prices. The top price election level was set at 90-100 percent of the expected market price. If the producer's yield fell below the elected coverage level, the producer received an indemnity payment equal to the product of the elected price coverage and the yield shortfall. This yield shortfall was determined by the amount that actual yields fell short of the farm's insured yield. Determination of the farm's insured yield initially was based on area average yields. This method increased the adverse selection problem as the risk pool became increasingly filled with farms that had loss-risks above the area average (Skees and Reed 1986). Consequently, after 1985 a farm's insured yield was based on the preceding ten years of the farm's actual production data.

Among government-provided insurance, crop insurance is unique in that it has not typically overcome adverse selection by mandating participation. Instead the Federal Crop Insurance Program has sought to entice producers to join by subsidizing premiums. From 1980 –

[2] barley, oats, corn, rice, sorghum, upland cotton, and wheat

1994 the subsidy reduced premiums by 30-percent for the 50- and 65-percent coverage levels, and by about 17-percent for the 75-percent level.

2.1 Two Disaster-Risk Mitigation Programs

The 1980 Act sought to create an insurance program that would replace disaster relief measures. However, Congress quickly established a precedent[3] of providing *ad hoc*, *ex post* disaster relief, thereby sustaining the pattern established in the 1970s of having two parallel mechanisms for dealing with crop-loss risk: crop insurance and disaster payments.

In spite of premium subsidies, enrollment in the Federal Crop Insurance Program was low and grew little through the 1980s. Table 1 contains measures of program size from 1981 – 2001. From 1981 – 1988 participation remained around 20-percent, increasing to 40-percent in 1989 only as a consequence of mandatory insurance for those receiving disaster payments in 1988.

The implicit guarantee of *ex post* disaster payments is a key reason for the historically low participation rates. The U.S. General Accounting Office (1989) reported that, "other federal disaster assistance programs provide farmers with direct cash payments at no cost to the farmers, resulting in the perception [among farmers] that crop insurance is unnecessary." As many others have pointed out (e.g., Just et al. 1999; Glauber 2004), those who did participate were adversely selected and more likely to collect indemnity payments. Table 1 contains the annual loss ratio (indemnities paid out divided by premiums collected), which averaged 1.47 in 1981 – 1994 and dropped below 1 only in 1994. The consistent payout of more indemnities than premiums collected from 1981 – 1994 supports the idea that those who chose to purchase crop insurance expected a positive return, while those who did not chose to rely on the costless disaster payments.

2.2 The Federal Crop Insurance Reform Act of 1994

The Federal Crop Insurance Reform Act of 1994 (FCIRA) constituted the most radical change in the Federal Crop Insurance Program since coverage was expanded to all counties in 1980. The 1994 Act established a mandatory minimum level of crop insurance coverage in order for producers to qualify for any other government-sponsored program, including subsidy and credit programs. For the first time, adverse selection in the crop insurance industry was addressed through mandatory participation. All insurable crops had to have at least catastrophic coverage, which insured production losses falling below 50% of expected yield, indemnified at 60% of the expected price of the insured crop. The Act facilitated compliance by authorizing a 100% subsidy on the catastrophic insurance premiums, requiring producers to simply pay a $50 administrative fee per crop insured.[4]

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[3] In 1986, a severe drought in the Southeast prompted Congress to pass supplemental disaster legislation. Then, in 1988 an extreme drought hit the Midwest, prompting congress to pass the Disaster Assistance Act of 1988 allocating $3.5 billion to producers who suffered crop loss. Congress subsequently passed 16 *ad hoc*, *ex post* facto disaster bills between 1989 – 2005.

[4] The administrative fee was capped at $200 per producer per county with an absolute cap of $600 per producer.

The Act also greatly expanded the options and subsidies for coverage beyond the catastrophic level, termed "buy-up" coverage. The maximum buy-up coverage level increased from 75- to 85-percent, and several tiers were added to the three coverage levels allowed earlier. The average subsidy also increased significantly. For example, the subsidy for the 65-percent yield coverage increased from 30-percent to 41.7-percent of the premium. The subsidy also varied by the coverage level under FCIRA, with the highest buy-up coverage level (85-percent) receiving a 13-percent subsidy.

As with the Federal Crop Insurance Act of 1980, the stated goal of FCIRA was to eliminate *ad hoc*, *ex post* disaster payments. In the subsequent three years this goal was generally accomplished with only $14 million in disaster payments made in 1995, $2 million in 1996, and none in 1997 (see table 1). However, when market conditions collapsed in 1998, Congress quickly reverted to providing disaster payments ($1.9 billion) in spite of 70-percent participation in the crop insurance program.

The FCIRA was responsible for a large increase in both the number of acres insured and the level of coverage. Figure 1 illustrates the total number of acres insured from 1981 – 2003. As figure 1 illustrates, the number of insured acres increased dramatically due to the 1994 Act. The total number of acres insured increased from 99.6 million in 1994 to 220.5 million in 1995. Of these 220.5 million acres, over half, 115 million acres, were covered by the newly mandated catastrophic coverage. Coverage levels also increased as farmers took advantage of increased subsidies.

Mandatory participation lasted only one year. Through the Federal Agriculture Improvement and Reform (FAIR) Act of 1996, Congress modified the crop insurance rules to allow farmers to opt out of catastrophic coverage. Table 1 and figure 1 both show a steady decline of insured acres after 1995 as farmers opted out until 1998 when 40 million fewer acres were insured.

3 Empirical Strategy

The objective of this paper is to investigate the role of government provided crop insurance in risk management by comparing the efficacy of disaster payments and crop insurance in reducing the failure rates of farms that receive government. I accomplish this by exploiting variation in weather and the exogenous change in the take-up of crop insurance induced by the Federal Crop Insurance Act of 1994.

Agricultural subsidy recipients were the target of the 1994 crop insurance mandate, and thus are the focus of my investigation. They also are both politically important and economically important. Farms that receive agricultural subsidies produce a substantial majority of the value of all agricultural output. Subsidized farms produce the major export crops, providing 39% of the world's corn, 19% of the world's cotton, and 28% of the world's wheat exports. These farms also are the objects of much policymaker attention. Over the past 25 years Congress has passed five major agricultural bills primarily aimed at this group of farmers, directing over $500 billion to their support.

The 1994 crop insurance expansion, which expanded coverage by 120%, provides a source of exogenous variation in crop insurance coverage. By exploiting this exogenous variation I overcome the endogeneity problem. Farmers who choose to purchase insurance coverage are likely to be different than their uninsured counterparts in many ways. Some differences will be unobservable to the econometrician, thereby resulting in an inconsistent estimate of the relationship between crop insurance and farm failure rates. Mandating that all farms participate in the crop insurance program overcomes this source of bias.

The 1994-1995 time period also provides a stark regime shift between politically-driven disaster payments and privately-administered crop insurance. In the decade prior to 1995 Congress had doled out over $10.3 billion in disaster payments. In 1993, one of the worst flooding years this century, farmers received nearly $2.5 billion in disaster payments. The disaster payments regime was particularly relevant in 1994. It was a relatively normal weather year in which indemnity payments were the lowest in the decade, yet over half a billion dollars in disaster payments were made. The regime shifted drastically in 1995 when farmers were required to have crop insurance, and disaster payments sharply decreased to $14 million. In 1996 disaster payments fell to $2 million, and in 1997 no disaster payments were made for the first time in over a decade[5]. This dramatic regime shift sets the stage to directly compare the efficacy of the two primary methods used to address losses caused by extreme weather events.

In spite of the dramatic regime shift, uniform application of the federal policy change makes it challenging to identify the relative effect of crop insurance with treatment-control comparisons. I overcome this obstacle in a novel way by using weather shocks to form the treatment and control groups. Although specific weather events are generally unpredictable, long-run weather patterns are not geographically random. For example, the odds of having snow and freezing temperatures in January in Ithaca, NY are pretty high. I address this issue by using conditional climate indices to come a close as possible to random assignment. These climate indices use the *county-month specific* weather distribution to calculate the conditional cumulative probability of an observed weather event. In other words, conditional on observing Tompkins County, NY in January, the climate index allows one to determine the likelihood of observing 48 inches of snow or more. Because the climate indices standardize the measure of an extreme event, all counties have an equal likelihood of being assigned to the treatment group, i.e. the treatment group is randomly selected.

Using this empirical approach, I estimate the effects of disaster relief. Under the assumption of random assignment, I estimate the effect of disaster assistance under each regime by simply comparing the average farm failure rate in the control group with that of the treatment group. I augment the simple differences with regression analysis in the event that the 'randomization' results in non-equivalent treatment and control groups. This will reduce sampling error and provide a check on the random assignment assertion. To further check the

[5] This dramatic shift was primarily caused by moving disaster payments from off-budget to on-budget, thereby requiring proponents of disaster payments to find cuts elsewhere in the budget to compensate for the disaster expenditures.

random assignment assertion I design a difference-in-differences estimator to provide an alternate estimate of the effects of disaster relief under the crop insurance regime.

Finally, these two exogenous events, weather and mandatory crop insurance, allow me to create a simple difference-in-differences estimator to calculate the relative effectiveness of crop insurance versus disaster payments at smoothing exogenous shocks by reducing farm failure rates. The identifying assumption of this estimation strategy is that there are no shocks in disaster stricken counties that are associated with the regime change but not caused by the regime change. If extreme weather events are truly randomly assigned over time, then the identifying assumption is a fairly weak one.[6]

4 Data

4.1 Farm Failure Rates

I use USDA administrative data obtained under the Freedom of Information Act in order to construct annual, county-level farm failure rates. The data consist of every payment made by the Farm Services Agency (FSA) from 1990 until 2001. The FSA is the U.S. Department of Agriculture's (USDA) administrative arm, which administers price and income support programs, as well as disaster relief programs. Although the data are not explicitly an enumeration of every farm in the United States it does contain information on the population of interest, every farm that received agricultural subsidies. If a farm is observed at two points in time, I extrapolate the farm's existence during the intervening period. If a farm drops out of the dataset and is never observed again, I label that farm as having failed in the last year observed. A key feature of these data is that in 1996 virtually all farms that qualified for subsidies received subsidy payments[7]. Hence, farms that may have chosen to opt-out of the subsidy program in 1994 or 1995 (when the participation rate was about 85%) are not counted as failures. Figure 3 illustrates the annual farm failure rate for this population.

4.2 Disaster Classification

The exact definition of an agricultural disaster is nebulous at best. *Ex post* measures such as crop yield loss presumably demonstrate the effects of weather shocks, but these measures are also determined by farmer behavior, making them endogenous to the question at hand. A much

[6] A means of addressing concerns about this assumption is to compare the outcomes of subsidized crop farms to farms in the same county that were unaffected by the crop insurance reforms. Two groups that qualify as within-treatment-controls are farms that primarily raise livestock and farms that grow non-insured crops, i.e. crops for which insurance is unavailable through the Federal Crop Insurance Program, typically fruits and vegetables. Livestock farms did not experience the crop insurance regime shift; they continued to qualify for the Livestock Emergency Assistance, a disaster payment-type program. Non-insured crops had a slight change to their disaster payments mechanism, but it was essentially the same. (See Lee et al. (1996) for discussion of the differences.) Performing this difference-in-differences-in-differences estimation requires data on livestock or non-insured crop farm failure rates, which are unavailable.

[7] This feature is important. Farms may temporarily drop out of the dataset without having actually failed, but a failed farm cannot temporarily show up in the data. This asymmetry potentially induces one-sided measurement error in the dependent variable. Since virtually all farms are observed in 1996 the measurement error caused by some farms temporarily opting out is dramatically reduced.

more satisfying classification is to quantify weather shocks as they occur. However, the heterogeneity in climate makes it impossible to use temperature and precipitation directly. Ten inches of rain in July in Florida will have a much different effect than ten inches in Montana. Therefore, in classifying drought and excess precipitation I employ the Palmer Drought Severity Index (PDSI) and the Standardized Precipitation Index (SPI). These indices are widely used by climatologists. For example, the U.S. Drought Monitor and state drought monitors use these indices to monitor drought conditions, the National Weather Services Climate Prediction Center uses the PDSI as their primary measure of drought, and disaster legislation often uses the PDSI to trigger disaster declarations. The indices also allow one to easily and directly compare weather shocks across different climates, e.g. Florida and Montana. The indices also provide a standardized measure of weather extremes. By these measures a farm in drought-prone West Texas is no more likely to experience a 'disaster' than a corn farm in Iowa.

4.2.1 Precipitation Indices

The Standard Precipitation Index provides a standardized measure of precipitation relative to the county-month specific time-series distribution of precipitation. The SPI is essentially a z-statistic constructed by transforming the location-specific time-series precipitation distribution into a standard normal distribution. One can then confidently speak about the likelihood of an event at least as extreme as the one observed and make geographic comparisons of precipitation-related weather events. The units of the precipitation distribution can be varied. If one were interested in long run precipitation anomalies one could look at the distribution of one- or five-year total precipitation. Because agriculture is very sensitive to short run weather shocks, I chose to examine the two-month total precipitation distribution for this analysis. The first panel of table 2 contains the event scale commonly associated with the SPI.

The Palmer Drought Severity Index incorporates temperature, precipitation, soil characteristics, and location to develop a supply and demand model for water. A drought is classified by the extent of excess demand for water, while excess wetness classification depends on the excess supply of water. The PDSI is a widely used measure of drought that considers the rainfall history, making it less sensitive to transitory events than the SPI. However, since agriculture responds to short-term transitory weather shocks, I also incorporate an index used to create the PDSI, the moisture anomaly index, generally know as the "Z" index. The Z index is the difference between the actual precipitation that fell in a specific month and the amount of precipitation needed to maintain normal soil moisture, adjusted for the climatic characteristics of the location. Essentially the Z index can be used to show how wet or dry it was during a single month without regard to recent precipitation trends. The commonly used classification system for the Z-Index and the PDSI are shown in the panel B and C respectively of table 2.

Using Unix programs available from the National Agricultural Decision Support System and the National Drought Monitor, I calculate the PDSI, its components, and the SPI for each county in the United States. The publicly available datasets typically report the PDSI and the SPI at the climate division, a level of geography than encompasses multiple counties. Climate division data are best used "to assess large-scale climatic features or anomalies with respect to a long period or century-scale perspective" (Guttman 1995). Although agriculture certainly suffers from such large-scale events, even smaller scale, relatively local weather events can have adverse effects. In order to exploit the smaller scale variation in weather, I calculate the PDSI and the SPI on the county level by using county-level weather data derived from the Parameter-elevation Regressions on Independent Slopes Model (PRISM) and county-level soil characteristics from the State Soil Survey Database (STATSGO)[8].

The PRISM modeling system generates estimates of precipitation and temperature at 4x4 kilometer grid cells for the entire United States. These estimates are based upon data collected by the National Oceanic & Atmospheric Administration (NOAA) Cooperative Weather Stations at over 3,000 locations nationwide from 1970 – 2001. In order to focus on the weather occurring on cropland these data are used in conjunction with data on the land use within each 4x4 km grid to calculate the average temperature and total precipitation for cropland.

The PDSI also requires a measure of the available water capacity (AWC) of the soil in the location where the temperature and precipitation are collected. The AWC is the amount of water that a soil can store that is available for use by plants (USDA-NRCS 1998). I calculate the average AWC for all cropland in each county using STATSGO data. STATSGO is a dataset collected by the US Department of Agriculture – National Soil Conservation Service containing soil characteristics, up to 6 layers deep, across the entire United States. In order to determine the characteristics of soil associated with cropland, I combine STATSGO with the National Resource Inventory (NRI), which collects data every five years on the land use of 844,000 points across the entire United States. I employ the land use data from 1992, the most recent year prior to the policy reform.

The final input into the PDSI calculation is the latitude corresponding to each data point. To obtain these data I use geographical information system (GIS) software to calculate the latitude of each county centroid.

4.2.2 Disaster Classification

Establishing objective disaster criteria is vital to the analysis that follows. Unfortunately, a myriad of factors contribute to disaster, of which weather is just one. Consequently, the climatology literature contains a set of possible criteria, but not a clearly defined standard. I draw upon that literature and rely upon the three indices outlined above in order to develop a 'disaster/non-disaster' classification. The PDSI, the Z-Index, and the SPI capture the short- to medium-term moisture events that are most applicable to agriculture. The National Climate Center uses these three indices as the core of its 'Short-Term Blend Weather Monitor' used to monitor weather events that could have significant effects on agriculture.[9] As noted earlier, table 2 contains the classification system of each index.

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[8] I am grateful to Olivier Deschenes and Michael Greenstone for generously providing the PRISM data used in this analysis.

[9] http://www.cpc.ncep.noaa.gov/products/predictions/experimental/edb/droughtblend-access-page.html

I ultimately use all three indices in order to establish the disaster classification. I calculate a county specific index for each month of the year. Because of my focus on extreme events I calculate the most extreme positive value of a county's index across all twelve months within a year, and I calculate the most extreme negative value of a county's index across all twelve months. Disasters occurring during the growing season have a significantly greater impact on agriculture than disasters during the non-growing season. Therefore I limit my focus to extreme index values occurring between May and October. Once I calculate the relevant extremes, I classify a county as having experienced a disaster if the PDSI and the Z-Index both exceed the 'severe' threshold on their respective scales, and the SPI value has a less than 5-percent likelihood. These criteria result in 795, 355, and 476 counties classified as disaster counties in 1993, 1994, and 1995 respectively.

The cross-sectional distributions of the moisture indices are shown in table 3. For the question at hand the interesting part of the distribution is not the center, as is usually reported, but the tails, i.e. the extreme events. In order to take a closer look at the tails, the upper panel of table 3 presents the 5^{th}, 15^{th}, 85^{th}, and 95^{th} percentiles. The lower panel of table 3 shows the average of each county's annual monthly-maximum index value and the average of each county's annual monthly-minimum index value for 1993, 1994, and 1995. Each of the indices characteristics can be seen in table 3. The Z-Index is most responsive to monthly precipitation and registers the greatest number of extreme values. The PDSI is a medium-term measure that adjusts slowly, as demonstrated by the continual downward trend in the monthly maximum PDSI, even though both the Z-Index and the SPI increase in 1995. The SPI has responsiveness between the Z-Index and PDSI, being very responsive to significant weather events.

The three panels of figures 4, 5, and 6 each show the geographic distribution of the three weather indices in 1993, 1994, and 1995 respectively. These figures underscore the information from table 3: 1993 was an extremely wet year, whereas 1994 was a relatively normal year. Climatologically, 1993 and 1995 were fairly similar, wet years. In the analysis that follows I will demonstrate the comparison between 1993 and 1995 as well as 1994 and 1995.

5 Empirical Results

5.1 Overview

In this section I exploit two natural experiments in order to examine the 'survival smoothing'[10] effects of disaster payments and crop insurance, the two most heavily used means of crop-loss insurance. I create randomized experiments by taking advantage of exogenous extreme weather events. In both natural experiments examined below I rely on random weather events to classify counties into disaster (treatment) and non-disaster (control) groups.

Random assignment allows me to avoid the endogeneity concerns associated with directly analyzing the impact of disaster or indemnity payments on farm failure rates. Farmer

[10] I adapt this term from the consumption smoothing effects that are examined in the social insurance literature. Since I am focused on failure rates, I deem a constant failure rate across states of nature 'complete survival smoothing.'

behavior associated with adverse selection and moral hazard affect the loss-likelihood and thereby determine the size of the disaster or indemnity payment. This same behavior also is plausibly correlated with the propensity to fail, thereby resulting in a spurious, non-causal relationship between payments and failure rates. By relying on the random component of crop-loss payments I avoid these concerns.

In addition to calculating the survival smoothing effects of disaster payments and crop insurance, one would like to examine the absolute effects of these two programs on farm failure rates. For example, policy makers would benefit from knowing the decrease in farm failure rates when a farmer moves from an uninsured state to being covered by catastrophic crop insurance. Unfortunately for this investigation, there has not been a time when farmers have not been potentially covered by disaster payments, crop insurance, or both.[11] Nevertheless, because of the virtual elimination of disaster payments and the increased insurance coverage in 1995 I can compare the *relative* effectiveness of these two programs. This is a fundamentally relevant policy question as Congress has operated these two programs in parallel intermittently for the past 35 years with frequent debate about the relative benefits.

In the analysis that follows I first examine each of these programs separately, and then I examine their relative effectiveness and test the survival smoothing hypothesis.

5.2 Randomized Experiments

5.2.1 Randomization

Random weather shocks play an intricate role in agricultural yield reduction. The type, severity, and timing of weather events interact in complicated, non-linear ways to influence output (Roberts and Schlenker, 2009). For example, a wet spell can have dramatically different effects on wheat yield if it occurs in early May instead of later June. Consequently, it is very difficult to develop a single metric to quantify a disaster. In order to ensure that the classification used in this paper corresponds to actual yield losses, I present the average per-acre disaster payment and the average proportion of crop liabilities indemnified for each treatment and control group.

Panel A of table 5 reports the average per-acre disaster payments in 1993 and 1994 for the disaster and non-disaster counties. The standard errors are in parenthesis, and the group size is in brackets. The disaster/non-disaster difference is also presented, along with its standard error. The average per-acre disaster payment for disaster counties in 1994 was \$5.11. In 1993 the amount was nearly double that at \$10.34, due to the worst flooding in the Midwestern United States this century. For the non-disaster counties the average per-acre disaster payment was \$2.90 and \$8.54 for 1994 and 1993 respectively. In both cases the disaster counties receive significantly greater disaster payments, validating the classification scheme.

The presence of substantial disaster payments in non-disaster counties underscores the importance of using exogenous weather events in this investigation. Although some of the

[11] In future work I will exploit yet to be obtained data and the dramatic expansion in crop insurance availability due to the 1980 Federal Crop Insurance Act to answer this question.

imperfect correlation between disaster payments and weather is surely due the complicated relationship between yield and weather, moral hazard effects and fraud provide an additional, more insidious explanation for the magnitude disaster payments to non-disaster counties. A somewhat less nefarious explanation is also viable. Disaster payments require Congressional action, and the political economy may result in large "disaster" payments directed to the constituents of key politicians. Garrett et al. (2003) demonstrate that between 1992 and 1999 about $7 billion of disaster aid was the result of political influence rather than due to disaster losses. This political economy may interact with moral hazard to magnify the effects. Others also have noted that counties that do not objectively appear to experience a disaster receive considerable disaster payments (Lee et al. 1996).

Panel B of table 5 demonstrate that disaster counties received greater indemnities as a proportion of total liabilities than did non-disaster counties. In 1995 11.2-percent of crop insurance liabilities were indemnified in disaster counties, compared with 8.2 percent in non-disaster counties. This again shows high, but imperfect, correlation between actual weather events and compensated losses.

In a randomized experiment, the treatment groups should be statistically similar. Table 4 the disaster and non-disaster county characteristics as measured in the 1992 Census of Agriculture. With a few rare exceptions, the treatment and control groups look statistically identical, further supporting the quasi-random experimental design.

5.2.2 Disaster Payments

Using the quasi-random experiment described above I evaluate the effect of *ad hoc* disaster payments on farm failure rates by simply comparing the average farm failure rate of the randomly assigned disaster counties to the average farm failure rate of the non-disaster counties. I make this comparison in two ways. First, table 5 panel C shows the averages failure rate of each group and the failure rate difference between the two groups. The standard errors are displayed in parentheses, and the group size is in brackets. The average failure rate in non-disaster counties is 6.5-percent in 1994 and 5.4-percent in 1993. The average failure rate in disaster counties is 5.9-percent and 5.0-percent in 1994 and 1993 respectively. Both the 1994 failure rate difference between groups and the 1993 difference show that under the disaster payments regime farms were slightly *less* likely to fail when hit by a disaster. The difference is small, but statistically significant, suggesting that disaster payments help sustain farms that otherwise would fail, regardless of whether they faced a disaster. In terms of survival smoothing, these findings suggest that disaster payments are not simply a substitute for other means of self-insurance. Clearly, government intervention aids in smoothing temporary shocks.

An alternative method for analyzing this experiment is with an ordinary least squares regression. This approach provides a check on the contention that treatment is quasi-random. Under true randomization other observed county characteristics should not influence the estimate, but the sampling variability should decrease when conditioning on covariates. Panel A in table 6 lays out the regression results using the county-crop mix as controls. The regression results are consistent with the simple differences outlined above, although the estimate changes somewhat with the inclusion of controls, suggesting some caution should be used when interpreting this in a strictly experimental sense.

Although disaster payments provided the vast majority of assistance in 1993 and 1994, it should be noted that the disaster payments regime included some farms that also held crop insurance. Disaster payments were more than twice the net indemnities (indemnities minus premiums) paid by crop insurance in 1993, and net indemnities were zero in 1994. Hence, the conclusion that disaster payments provide for survival smoothing is a statement about the entire regime, in which *ex post* disaster payments play a dominant role.

5.2.3 Crop Insurance

I also examine the influence of crop insurance on farm failure rates through a quasi-randomized natural experiment. As with the experiment investigating the disaster payments regime, I categorize counties into disaster and non-disaster groups using exogenous, random weather events. The lower half of panel C in table 5 contains the results of this experiment. The results from this experiment are generally consistent with an increased failure rate when faced by a disaster under the crop insurance regime. Farms with crop insurance have a 1.3 percentage point increased failure rate when hit by a disaster. This raises the average failure rate to 8.3-percent from a 7-percent failure rate when not hit by a disaster.

These findings suggest that crop insurance fails to provide complete survival smoothing. High deductibles provide a plausible explanation. Deductibles ranged from 35-percent to 50-percent of production. The most widely held coverage level, the mandated catastrophic coverage, had a 50-percent of production deductible. Such a large deductible possibly provided an insufficient buffer for some farmers, resulting in permanent effects of large, temporary shocks (Basker, 2003).

As with the disaster payments regime, I use ordinary least squares regressions to augment the experimental approach by including covariates in the analysis. The third row of panel A in table 6 contains the regression estimates. Once covariates are included in the analysis the coefficient decreases to 0.7, becoming statistically insignificant in spite of the slightly smaller standard error. This estimate signifies nearly no change in failure rates due to disaster under the crop insurance regime, although the original, simple-difference estimate is still within the confidence interval.

5.3 Relative Effectiveness

One would like to use the 1994-1995 policy change that more than doubled the rate of insurance coverage to examine the absolute effect of crop insurance coverage. As noted earlier, this is unfortunately not possible because *ad hoc*, *ex post* disaster payments were the norm prior to the 1994 Act. Instead, it is informative to compare the effectiveness of the disaster payments regime to that of the crop insurance regime. Knowing their relative effectiveness at decreasing farm failures in the face of disaster is the first step to understanding the incentive effects of each regime and to designing an optimal government-provided crop-loss insurance scheme.

I evaluate the relative effectiveness of the two regimes by comparing the outcomes of the previous two quasi-random experiments. Panel C in table 5 contains the results of the experiments in 1993, 1994, and 1995. I report the relative effects of the two regimes in the last two rows of panel C by taking the difference between each of the disaster payment regime results and the 1995 crop insurance regime results. These difference-in-differences estimates demonstrate the relative effectiveness of these two programs.

The results of these comparisons are remarkably similar. Relative to the 1993 regime, farms suffering a disaster in 1995 are 1.7 percentage points more likely to fail. That likelihood is 1.9 percentage points when 1994 is the base period. Both of these results are statistically significant.

I extend my analysis of the relative effects controlling for observable county characteristics in a regression framework. As with the quasi-random experiments, any failure of the randomization resulting in treatment group heterogeneity could be problematic. Through regression analysis I also address the concern that the composition of the treatment group is allowed to differ between the two periods by controlling for other observables that affect failure rates. The regression equation has the following form:

$$F_{it} = \alpha + \beta_1 X_{it} + \beta_2 \tau_t + \beta_3 \text{disaster}_{it} + \beta_4 (\tau_t \times \text{disaster}_{it}).$$

In this equation i indexes counties and t indexes years (1 if after the policy change, 0 if before). F_{it} is the farm failure rate, X is a vector of observable county characteristics, τ is a fixed time effect, and *disaster* is a dummy variable for disaster counties in either regime.

The form of the regression resembles the typical difference-in-differences regression. However, the interpretation of the coefficients is slightly different because the treatment group is not the same in both periods. The time fixed effect controls for time-series changes in the failure rate. The disaster variable captures the effect of a disaster in the first period while the second order interaction term captures the relative effect between the two regimes. The set of covariates includes the proportion of cropland planted to 12 different crops.

Panel B of table 6 reports the coefficients of the interaction term for the various criteria. Controlling for covariates, I cannot reject the hypothesis that there is no change in farm failure rates when moving from the 1993 disaster payments regime to the 1995 crop insurance regime. However, relative to the 1994 disaster payment regime, a farmer is 1.2 percentage points more likely to fail with crop insurance in 1995 after controlling for crop mix. This estimate is similar to the point estimate of 1.9 percentage points from the simple difference-in-differences estimate.

6 Interpretation and Conclusion

The analysis above found a decreased failure rate for the disaster payments regime, and less than complete smoothing for the crop insurance regime. I estimate that, relative to the disaster payments regime, farm failure rates increase by between 1.7 – 1.9 percentage points under the crop insurance regime. From an average failure rate of 7.2-percent this change represents a 30-percent increase in the likelihood of failure when faced with a natural disaster under the crop insurance regime.

This is a surprising finding for several reasons. First, the ultimate structure of *ex post* disaster payments and mandatory catastrophic crop insurance is very similar. *Ex post* disaster payments provided coverage of loss greater than 65-percent of yield at 60-percent of the expected price. The catastrophic coverage was less generous, covering only 50-percent of crop lass at 60-percent of the expected price. This reduced generosity might play a factor in the findings, but one would expect the overall coverage increase due to substantially increased premium subsidies to have had an off-setting effect.

An alternative explanation could be in the moral hazard incentives that are likely more substantial with an *ex ante* insurance plan. *Ex ante* insurance provides incentives for the farmer to shirk early on in the growing season, when reduced tillage, chemical treatment, or fertilizer will have the greatest impact. Coverage uncertainty under the *ex post* disaster payments regime reduces the incentives for moral hazard behavior. Even if disaster payments were implicitly anticipated, the Congressional action necessary to activate coverage is likely somewhat capricious. Under this sort of coverage, the moral hazard incentives might only set in late in the season when it became certain that Congress would act.

Delaying moral hazard may be a factor contributing to the greater effectiveness of the disaster payments regime. More data are required in order to investigate this explanation. Obtaining data on fertilizer and chemical input will help in evaluating these claims.[12]

Alternative explanations are also viable. Fraud might play a role if it is better addressed under the crop insurance regime than under *ex post* disaster payments. The Federal Crop Insurance Program is operated primarily through private insurers that are reinsured by the U.S. Department of Agriculture. The private insurers might be better at policing and weeding out fraudulent claims. If this is the case and if fraudulent claims are made by farms that are more likely to fail, then fraud could be a factor in the finding.

In other words, the greater likelihood of farm survival under the disaster payments regime is not necessarily a good thing. Perhaps the greatest cost of an *ad hoc*, *ex post* disaster payments program is in terms of the disutility of farmers forced to bear the *ex ante* risk of failure due to random weather events. Public policy will greatly benefit from research more closely examining the potential costs associated with these program structures, in addition to the moral hazard and adverse selection costs studied by others and the survival smoothing benefits outlined in this paper.

Although the absolute effects of crop insurance and disaster payments remain unknown, finding a positive relative effect allows me to conclude that disaster payments do provide survival smoothing and do not perfectly crowd out other means of risk mitigation. This finding suggests that there is a significant role for government-provision of crop-loss insurance.

[12] The author is currently pursuing use of confidential survey data in order to address this issue.

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Table 1. Crop Insurance and Disaster Payment Details							
Year	Policies (thousands)	Acres (mil)	Participation Rate	Total Premium ($ mil)	Indemnity ($ mil)	Total Loss Ratio	Crop Disaster Payments ($ mil)
1981	416.8	45.0	16	376.8	407.3	1.08	306
1982	386.0	42.7	15	396.1	529.1	1.34	115
1983	310.0	27.9	12	285.8	583.7	2.04	1
1984	389.8	42.7	16	433.9	638.4	1.47	0
1985	414.6	48.6	18	439.8	683.1	1.55	0
1986	406.9	48.7	20	379.7	615.7	1.62	556
1987	433.9	49.1	22	365.1	369.8	1.01	10
1988	461.0	55.6	25	436.4	1,067.6	2.45	3,386
1989	949.7	101.7	40	819.4	1,215.3	1.48	1,500
1990	893.7	101.3	40	835.5	1,033.6	1.24	6
1991	706.2	82.3	33	736.4	958.5	1.30	960
1992	663.1	83.1	31	758.7	922.5	1.22	872
1993	678.8	83.7	32	755.6	1,653.4	2.19	2,461
1994	800.4	99.6	38	948.9	600.9	0.63	577
1995	2,039.2	220.6	41/85	1,543.0	1,566.5	1.02	14
1996	1,623.3	205.0	44/76	1,838.4	1,491.0	0.81	2
1997	1,320.1	181.9	43/67	1,773.8	990.1	0.56	0
1998	1,242.4	181.7	46/69	1,874.2	1,659.3	0.89	1,913
1999	1,287.9	196.3	53/73	2,304.4	2,416.1	1.05	1,452
2000	1,323.2	206.5	59/76	2,540.1	2,591.0	1.02	2,348
2001	1,297.9	211.8	63/78	2,961.9	2,959.4	1.00	0
2002	1,259.4	215.5	66/80	2,915.9	4,054.0	1.39	2,145

Notes: Source: U.S. Department of Agriculture - Risk Management Agency.
Participation rate calculated as acres insured as percent of eligible acres. For 1995 - 2002, the first number is the participation in "buy-up" and the second number is total parti

Table 2. Climate Indices

Index Value	Classification
A. Standardized Precipitation Index	
2.0+	Extremely Wet
1.5 to 1.99	Very Wet
1.0 to 1.49	Moderately Wet
-0.99 to 0.99	Near Normal
-1.0 to -1.49	Moderately Dry
-1.5 to -1.99	Severely Dry
-2.0 and less	Extremely Dry
B. Moisture Anomaly (Z) Index	
3.50+	Extremely Wet
2.5 to 3.49	Very Wet
1 to 2.49	Moderately Wet
-1.24 to 1	Near Normal
-1.25 to -1.99	Moderate Drought
-2.0 to -2.75	Severe Drought
-2.75 and less	Extreme Drought
C. Palmer Drought Severity Index	
4.0+	Extremely Wet
3.0 to 3.99	Very Wet
2.0 to 2.99	Moderately Wet
1.0 to 1.99	Slightly Wet
0.5 to 0.99	Incipient Wet Spell
0.49 to -0.49	Near Normal
-0.5 to -0.99	Incipient Dry Spell
-1.0 to -1.99	Mild Drought
-2.0 to -2.99	Moderate Drought
-3.0 to -3.99	Severe Drought
-4.0 and less	Extreme Drought

Table 3. Climate Indices' Distributions

	June 1995			
	5%	15%	85%	95%
SPI	-1.21	-0.59	1.6	2.03
PDSI	-2.67	-1.41	2.93	3.68
Z-Index	-2.29	-1.43	2.42	4.1

	1993	1994	1995
Minimum Monthly			
SPI	-1.29	-1.38	-1.47
	(0.61)	(0.49)	(0.58)
PDSI	-0.29	-0.50	-0.71
	(1.85)	(1.86)	(1.82)
Z-Index	-1.81	-2.05	-2.03
	(0.96)	(0.63)	(0.77)
Maximum Monthly			
SPI	1.54	1.38	1.48
	(0.69)	(0.65)	(0.52)
PDSI	2.56	2.04	1.87
	(1.88)	(1.83)	(1.67)
Z-Index	3.43	3.04	3.28
	(2.02)	(1.77)	(1.59)

Notes: The climate indices are: the Standardized Precipitation Index (SPI), the Palmer Drought Severity Index (PDSI), and the Palmer Moisture Anomaly (Z) Index (Z-Index). The climate indices are calculated for each month of the year. The upper panel contains the indicated percentiles of each index in June, 1995. The cells in the lower panel contain the cross-sectional average of the minimum and maximum value across all 12 months. The standard deviations are in parentheses. See table 3 for the magnitude classification of each index.

Table 4. Characteristics of Disaster and Non-Disaster Counties
Disaster Criteria--Palmer Moisture Anomaly (Z) Index &
Palmer Drought Severity Index & Standardized Precipitation Index

	Disaster Payments (1993)		Disaster Payments (1994)		Crop Insurance (1995)	
Characteristic	Disaster	Non-Disaster	Disaster	Non-Disaster	Disaster	Non-Disaster
Farm Size (acres)	636.722	741.739	521.361	732.923	885.787	666.612
Land Value ($/acre)	956.25	1,227.76	1,093.90	1,160.12	1,056.58	1,170.80
Sales ($)	90,673.57	84,168.31	77,850.50	87,233.88	97,798.61	83,785.73
Proportion of Cropland						
Barley	0.022	0.037	0.022	0.033	0.033	0.031
Corn	0.329	0.233	0.257	0.280	0.228	0.261
Cotton	0.006	0.074	0.095	0.053	0.037	0.082
Soybeans	0.252	0.174	0.154	0.201	0.186	0.205
Oats	0.028	0.040	0.044	0.036	0.035	0.030
Sorghum	0.043	0.024	0.014	0.030	0.042	0.023
Wheat	0.224	0.213	0.182	0.207	0.286	0.181
Rice	0.003	0.012	0.001	0.012	0.006	0.011
Beans	0.003	0.008	0.007	0.007	0.008	0.006
Sunflowers	0.007	0.002	0.010	0.004	0.011	0.004
Other	0.017	0.048	0.089	0.031	0.033	0.039
Proportion of Farms						
Cattle	0.553	0.559	0.553	0.557	0.593	0.550
Beef Cows	0.416	0.438	0.419	0.433	0.454	0.427
Milking Cows	0.076	0.069	0.084	0.069	0.085	0.068
Hogs and Pigs	0.152	0.073	0.101	0.094	0.101	0.094
Sheep and Lambs	0.051	0.044	0.031	0.048	0.053	0.045
Layers	0.039	0.051	0.048	0.047	0.050	0.047
Broilers	0.006	0.015	0.016	0.012	0.010	0.013
Proportion of Farmland						
Rented Farmland	0.449	0.363	0.336	0.395	0.398	0.386
Irrigated Farmland	0.047	0.074	0.046	0.069	0.085	0.062
Farmer Characteristics						
Experience	20.6	19.4	19.8	19.8	20.3	19.7
Age	52.4	53.9	53.5	53.4	53.4	53.4
Full Owner	0.514	0.587	0.576	0.558	0.530	0.566
Part Owner	0.356	0.306	0.327	0.324	0.351	0.319
Tenant	0.131	0.107	0.098	0.119	0.119	0.115
Primary Occupation Farming	0.612	0.522	0.539	0.556	0.591	0.546
Family Farm	0.856	0.854	0.874	0.852	0.855	0.855
Partnership	0.095	0.097	0.086	0.098	0.092	0.098
Family Corporation	0.039	0.037	0.029	0.038	0.041	0.036
Corporation	0.004	0.005	0.004	0.004	0.004	0.004

Notes: Data for all groups are from the 1992 Census of Agriculture, except data for crops data which are from the U.S. Department of Agriculture-National Agricultural Statistics Service *Crop County Files* for each of the years listed. See text for criteria used to assign counties to disaster and non-disaster groups.

Table 5. Quasi-Random Experiments:
The Effects of Disaster Payments and Crop Insurance on Farm Failure Rates
Disaster Criteria--Palmer Moisture Anomaly (Z) Index,
Palmer Drought Severity Index & Standardized Precipitation Index

Regime	Disaster	Non-Disaster	Disaster/Non-Disaster difference
A. Per-Acre Disaster Payments			
Disaster Payments (1993)	10.336	8.567	1.770
	(0.449)	(0.429)	(0.621)
	{795}	{2007}	
Disaster Payments (1994)	5.113	2.904	2.209
	(0.485)	(0.199)	(0.524)
	{355}	{2440}	
B. Proportion of Liabilities Indemnified			
Crop Insurance (1995)	0.112	0.082	0.030
	(0.007)	(0.003)	(0.007)
	{465}	{2239}	
C. Causal Effect of Disaster Payments and Crop Insurance on Farm Failure Rates			
Disaster Payments (1993)	0.050	0.054	-0.004
	(0.001)	(0.001)	(0.002)
	{795}	{2007}	
Disaster Payments (1994)	0.059	0.065	-0.006
	(0.002)	(0.001)	(0.002)
	{355}	{2440}	
Crop Insurance (1995)	0.083	0.070	0.013
	(0.005)	(0.002)	(0.005)
	{476}	{2314}	
1993 - 1995 Relative Effect			0.017
			(0.005)
1994 - 1995 Relative Effect			0.019
			(0.006)

Notes : Standard errors are given in parentheses. The disaster classification corresponds to the 'severe' classification of each climate index: Z-Index > 2.5 or < 2, PDSI > 3 or < -3, and SPI > 1.5 or < -1.5. Panel A contains the average dollars per acre in disaster payments for each group in the disaster payments regime. Panel B contains the ratio of indemnitied to liabilities for each group in the crop insurance regime. The cells in panel C contain the average farm failure rate for each the group during each regime.

Table 6. Treatment-Dummy Results
Across Regimes

Regime	Failure Rate	
A. Quasi-Random Cross-sectional Experiments		
Disaster Payments (1993)	**-0.004**	0.003
	(0.002)	(0.002)
Disaster Payments (1994)	**-0.006**	**-0.006**
	(0.002)	(0.002)
Crop Insurance (1995)	**0.013**	0.007
	(0.005)	(0.005)
Covariates	N	Y
B. Relative Program Effects		
1993 - 1995 Relative Effect	**0.017**	0.003
	(0.005)	(0.005)
1994 - 1995 Relative Effect	**0.019**	**0.012**
	(0.006)	(0.005)

Notes : White's heteroskedastic-robust standard errors are in parentheses. The dependent variable is the county-level farm failure rate. In panel A the coefficient is that on the 'disaster county' indicator in the cross-sectional analysis for each regime. Panel B contains the coefficient on the interaction term when comparing the two years. The covariates are the proportion of cropland planted to 12 different crop groups.

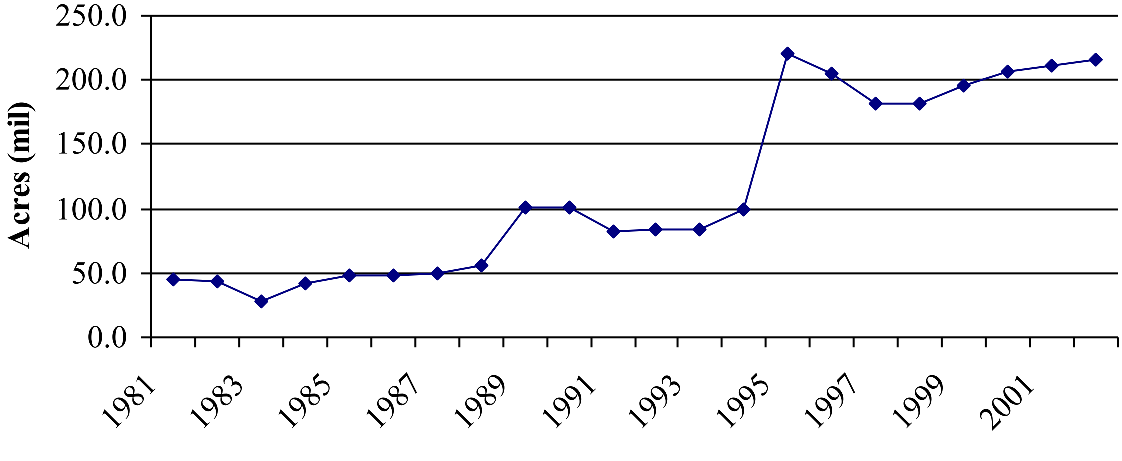


Figure 1 . Total Acres Covered by Crop Insurance

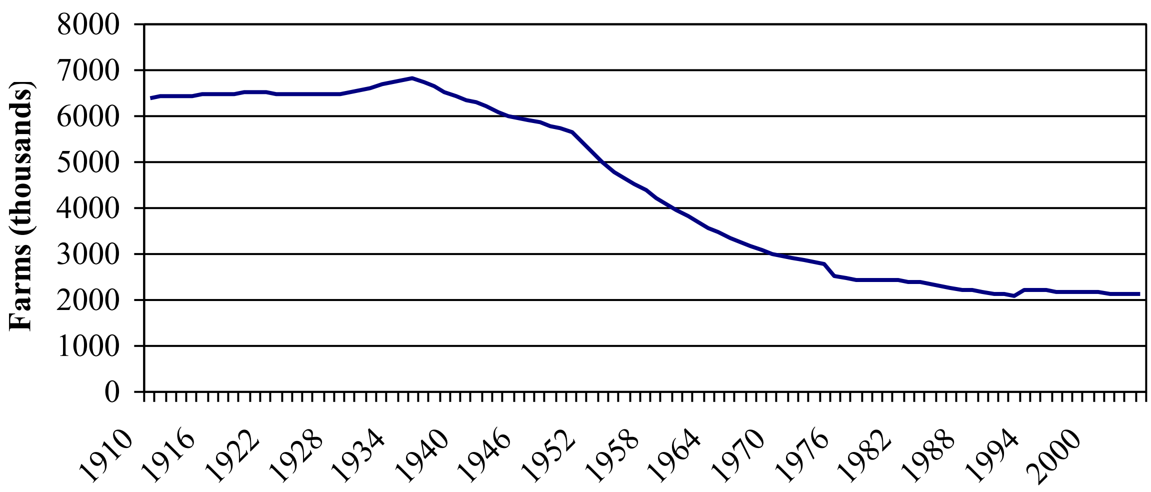


Figure 2 . Number of Farms, 1910 - 2004

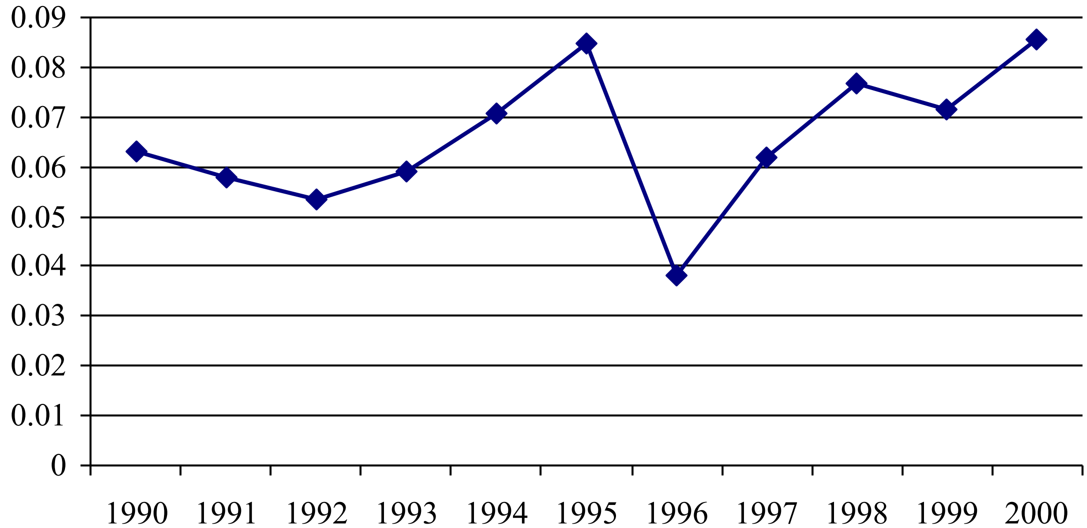
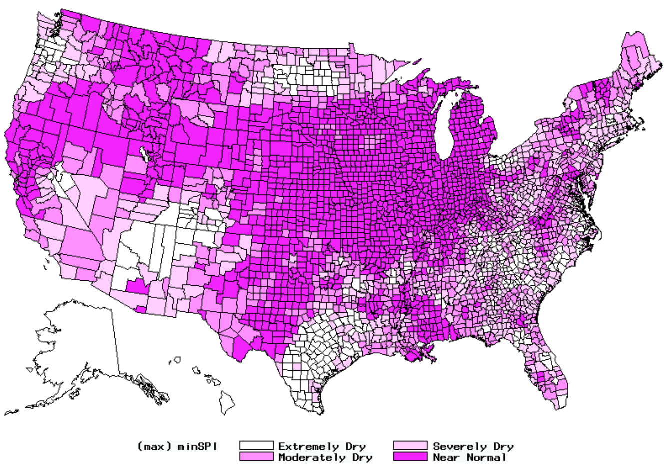


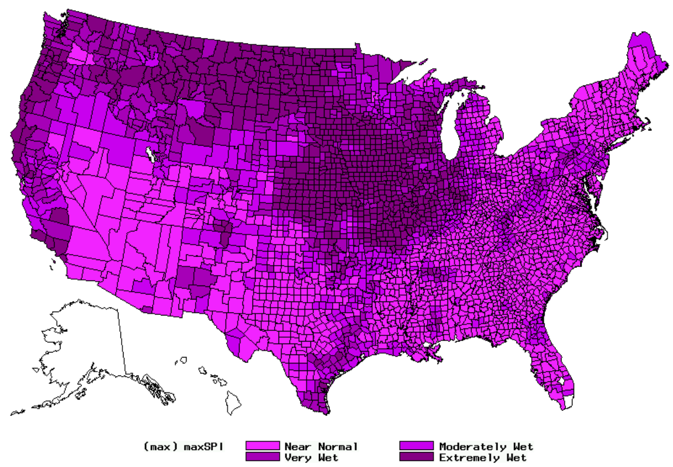
Figure 3. Farm Failure Hazard Rate

Figure 4. 1993 Geographic Distribution of Climate Indices

A. Standardized Precipitation Index

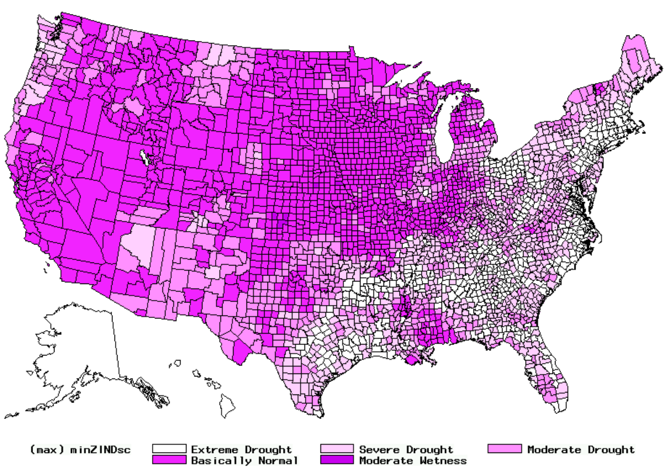
Monthly-Minimum	Monthly-Maximum

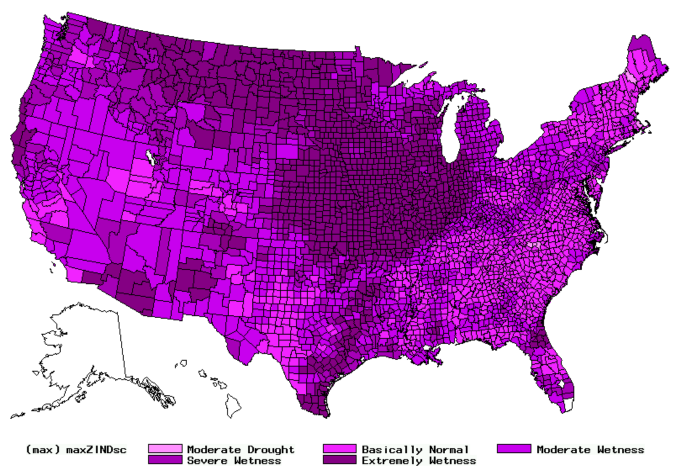




B. Moisture Anomaly (Z) Index

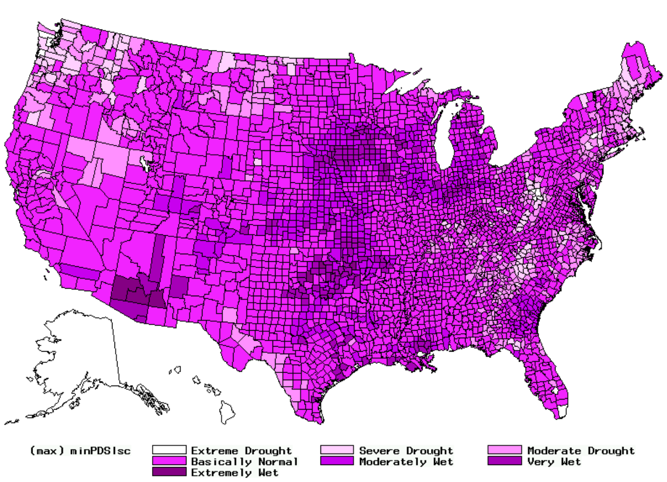
Monthly-Minimum	Monthly-Maximum





C. Palmer Drought Severity Index

Monthly-Minimum	Monthly-Maximum



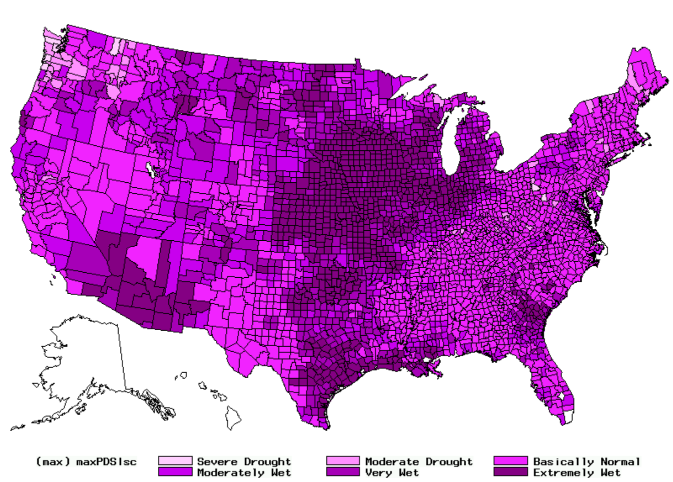
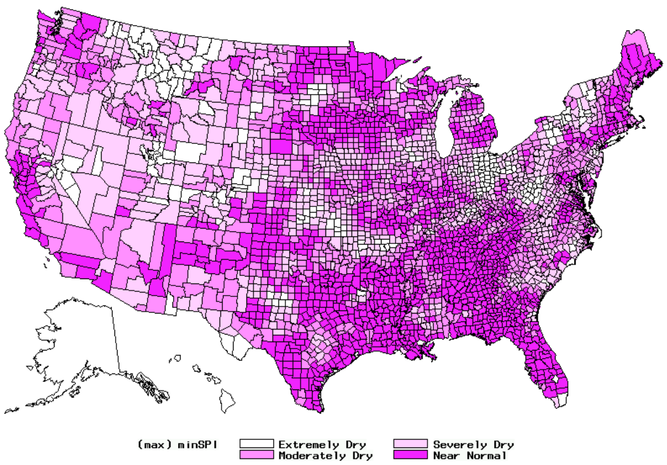
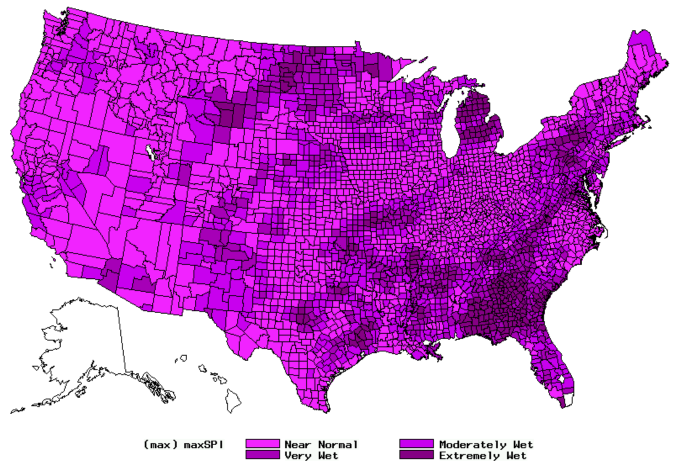


Figure 5. 1994 Geographic Distribution of Climate Indices

A. Standardized Precipitation Index

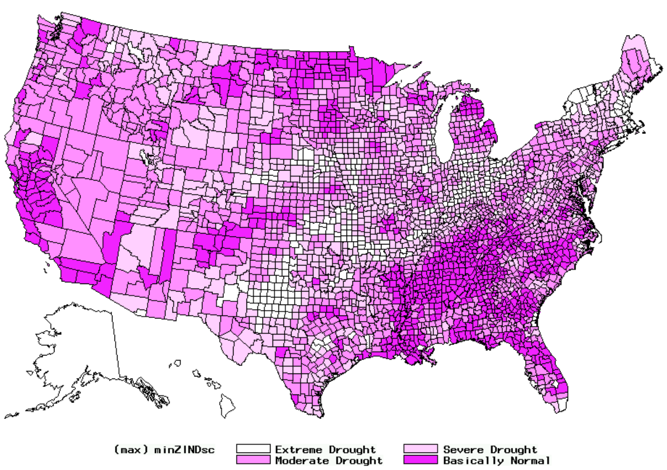
Monthly-Minimum	Monthly-Maximum

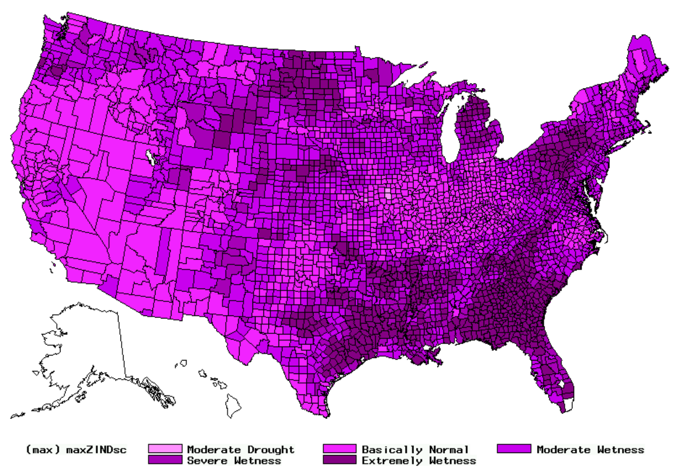




B. Moisture Anomaly (Z) Index

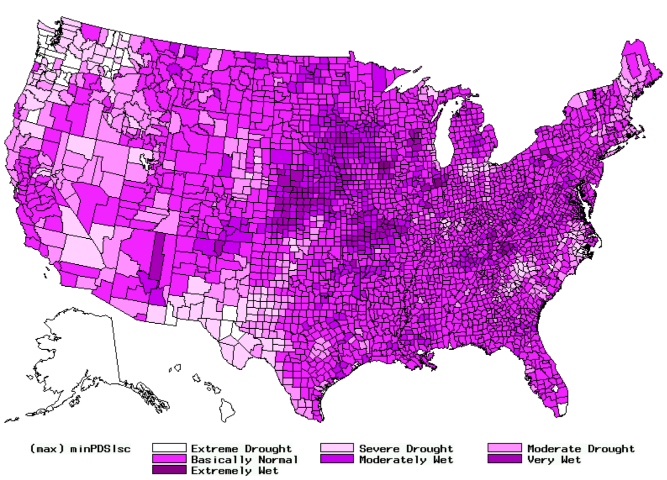
Monthly-Minimum	Monthly-Maximum





C. Palmer Drought Severity Index

Monthly-Minimum	Monthly-Maximum



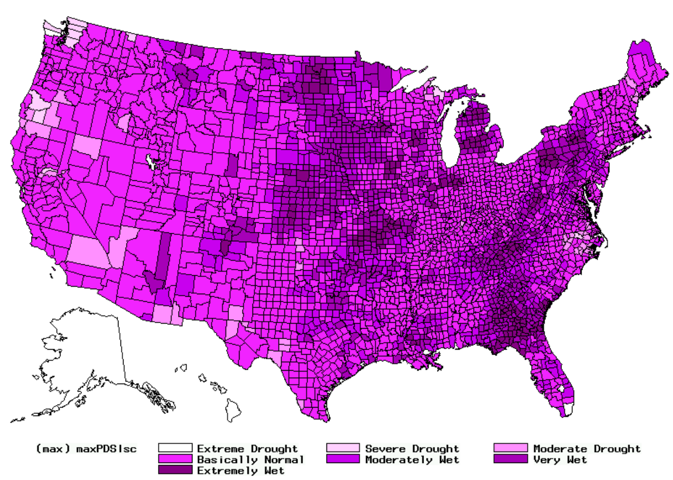
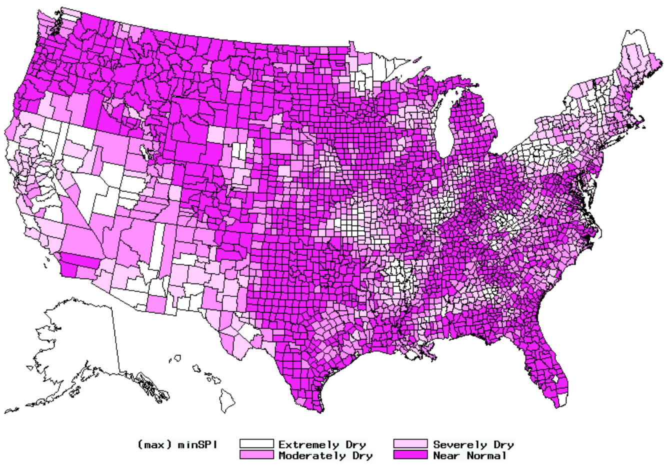
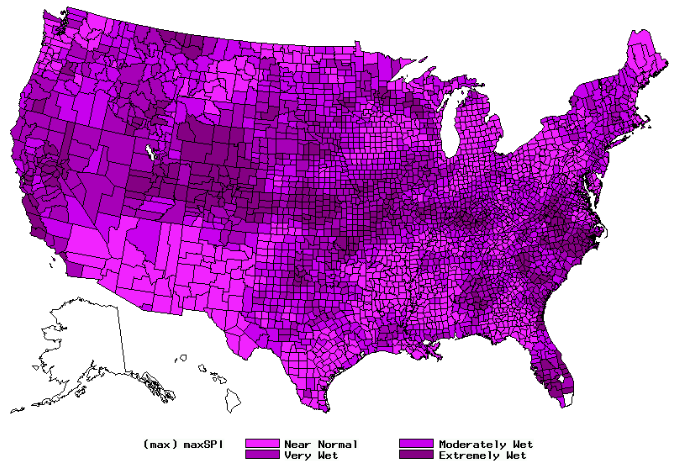


Figure 6. 1995 Geographic Distribution of Climate Indices

A. Standardized Precipitation Index

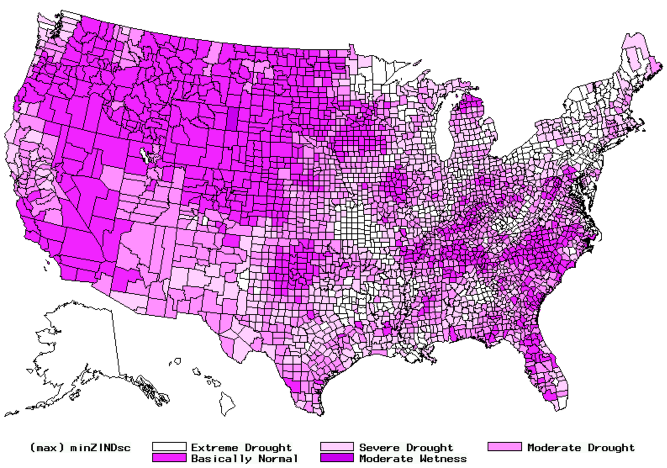
Monthly-Minimum	Monthly-Maximum

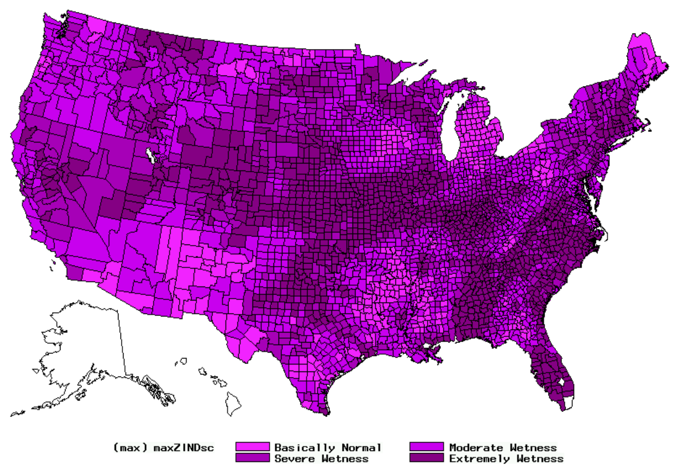




B. Moisture Anomaly (Z) Index

Monthly-Minimum	Monthly-Maximum





C. Palmer Drought Severity Index

Monthly-Minimum	Monthly-Maximum