THESIS

THE IMPACT OF HYDROMETEOROLOGICAL HAZARDS ON AGRICULTURE IN THE U.S. MIDWEST

Submitted by

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ABSTRACT

THE IMPACT OF HYDROMETEOROLOGICAL HAZARDS ON AGRICULTURE IN THE U.S. MIDWEST

Hydrometeorological hazards can have detrimental effects on agricultural production and farm income. This paper examines how growing season temperature extremes, droughts and flood events affect corn yields, soybean yields, net farm income and crop insurance transfers across 889 counties in the U.S. Midwest over 2002 to 2023. Weather shocks and crop yield losses are linked by a well established biological channel. However, farm income represents a richer set of responses and is more complex. Therefore, the income impact of hydrometeorological shocks do not always mirror yield impacts. Outcome variables may also respond differently to composite drought indices versus raw temperature and precipitation measures. The Palmer Z-index, flood events from the NOAA Storm Events Database, temperature bins and precipitation measures are used to explore the effect of these shocks on agricultural outcomes.

The study finds a robust association between days with average temperature above 30 degrees Celsius and reductions in corn and soybean yields of 3.1 percent and 2.7 percent per day respectively. By comparison, an additional five day period of moderate to extreme drought is associated with reductions in corn yields by 2.3 percent and soy yields by 2 percent. An additional day with average temperature above 30 degrees Celsius is associated with a reduction in farm operations income by $2.06 million per county - the largest negative association with income. However, it is not significantly associated with large insurance responses. By comparison, an additional moderate to extreme drought period is associated with an increase in insurance payments of over $1 million per county. The results suggest that insurance buffers moisture shocks more than heat.

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Chapter 1

Introduction

Extreme weather events pose great risk to agricultural production, farm income and the rural economies around the world. Among all of the classes of natural hazards, hydrometeorological hazards are among the most detrimental to agriculture. They can simultaneously affect crop yields (Schlenker and Roberts, 2009; Kuwayama et al., 2019; Rosenzweig et al., 2002), input cost (Fleming-Muñoz et al., 2023) and market prices (Lal et al., 2012) and these effects often interact with insurance and government support payments. In order to better understand climate resilience, better design agricultural policy and better evaluate long-run food system stability, it is crucial to understand how hydrometeorological shocks affect farm-level outcomes.

Previous research analyzing the impact of hydrometeorological extremes on agriculture have primarily focused on assessing the impacts of droughts, floods and temperature extremes on crop yields. Climate extremes, especially hydrometeorological shocks almost always lead to reduction of crop yields. However, the impact of climate shocks on farm income is considerably more complex for a variety of reasons. Farm income not only reflects the biological channel of impact through production losses but also market-mediated price adjustments, insurance indemnities, disaster assistance, and farmer adaptation along both intensive and extensive margins. The federal crop insurance program (FCIP) payments are triggered when operations or producers experience yield or revenue losses below guaranteed levels (USDA Economic Research Service, 2026). Therefore, the impact of hydrometeorological shocks on crop yields is different from the impact on farm income. However, there has not been sufficient research that seeks to disentangle these channels.

The paper examines the impact of growing season droughts with a Palmer Z-index of -2 to -3 (mild drought) or below -3 (moderate to extreme drought), growing season moisture with Palmer Z-index of +2 to +3 (mild wet/moisture) or above +3 (moderate to extreme wet/moisture), flood events from the NOAA Storm Events Database, temperature (six 5 degrees Celsius bins) and precipitation extremes on corn yield, soybean yield, farm income and insurance receipts. The Z-index categories are consistent with Gridmet classifications (University of California Merced, 2024). The paper also analyzes if insurance transfers and compositional adjustments mask underlying production losses. The sample comprises 889 counties across 11 Midwestern states. The focus is on corn and soybean as they are the two primary crops in the U.S. Midwest. Studies of a similar nature have focused on mostly drought impacts (Kuwayama et al., 2019) or temperature impacts (Roberts and Schlenker, 2011). This study conducts a parallel assessment of both droughts and flood events along with extreme temperature and precipitation.

The study divides the Z-index into four bins to understand if the impacts of the Z-index bins are symmetric and finds that different bins have different magnitudes and directions of association with agricultural outcomes. Temperature is also divided into bins to study the association of the number of growing-season days in each temperature bin with yield, net farm income and insurance payment outcomes. The parallel specifications also help us compare and contrast the estimates from a drought or soil moisture anomaly index versus a raw temperature-precipitation specification. The climate adaptation literature provides insight that responses to weather shocks are not uniform (Schlenker and Roberts, 2009; Burke and Emerick, 2016). It also states that there are crop specific vulnerabilities that are important - an example being corn's heightened sensitivity to extreme heat (Roberts and Schlenker, 2011).

Importantly, the study helps explore the channels through which the association of the Z-index, flood counts, extreme temperature and precipitation impact farm operator income. The hypothesized mechanism of the impact of hydrometeorological hazards on farm income can be through both biophysical or non-biophysical channels. Federal and private crop insurance, along with price effects and a variety of adaptation measures are hypothesized to buffer the impact of these hazards. Therefore, it is critical to understand not only the effect of these hazards on crop yields but also farm income and insurance payments.

It is evident from the results that hydrometeorological hazards are significantly associated with farm income losses and trigger compensatory crop insurance transfers, however, these losses vary with hazard type. Extreme heat days above 30 degrees Celsius (86 degrees Fahrenheit) in the defined growing season (June to September) is the dominant driver of these losses. It can be seen that these extreme heat days are associated with reductions in county-level operations income by \$2.06 million and producer income by \$1.98 million per additional day in that threshold. By direct contrast, we can see that moderate to extreme drought does not generate statistically significant income effects. A partial explanation of this divergence can be obtained from the insurance results. Moderate to extreme droughts are significantly associated with a large institutional response - estimated increase in insurance indemnities of \$1.14 million in RMA total indemnities, \$0.90 million in corn-specific indemnities and \$0.2 million in soy-specific indemnities per pentad of moderate to extreme drought exposure. By direct contrast, we can see that extreme heat (days with mean temperature of 30+ degrees Celsius) does not generate statistically significant insurance response indicating that extreme heat days are not compensated as much through the institutional pathway. Lastly, we can see that this 'income-neutrality' of moderate to extreme drought pentads does not take place in absence of crop yield damage - moderate to extreme drought reduces corn yields by approximately 2.3% and soy yields by approximately 2.0% per pentad. This all leads to suggest that the crop insurance programs studied have differing responses and income stabilization roles to different hydrometeorological hazards.

1.1 The Conceptual Model

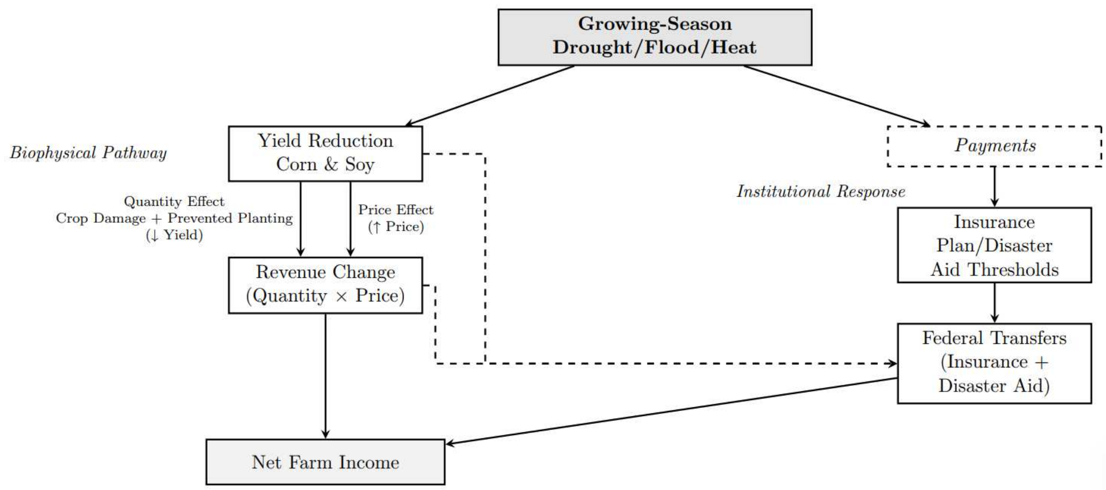

Figure 1.1: Pathways from Hazard Shocks to Net Farm Income

Figure 1.1 illustrates the two pathways through which growing season weather shocks are transmitted to net farm income - the biophysical pathway and the institutional response pathway. The biophysical pathway runs from yield reduction to revenue change through quantity effects and price effects. Yield reductions can happen in two ways - direct destruction of crops by the detrimental effects of the shocks or by prevented planting. These yield reductions directly affect net revenue but are offset by price effects to varying extents because supply shocks raise prices. Changes in net revenue directly affect net farm income.

The institutional response pathway runs parallel to the biophysical pathway to some extent. The figure shows how federal response to these shocks ultimately affects net farm income. The federal crop insurance payments are triggered when the revenues or yields fall below a specified guaranteed amount. Disaster payments for the agricultural sector are primarily handled by the USDA Farm Service Agency (FSA). There are multiple programs that offer disaster payments including loans for droughts. Some notable ones are Supplemental Disaster Relief Program (SDRP) and USDA Secretarial Disaster Designation. These disaster payment programs depend on specific criteria tied to the US Drought Monitor classifications - usually a D2 classification of drought for at least eight consecutive weeks or D3/D4 for any amount of time. There are also other programs that are based on crop yields, such as the Noninsured Crop Disaster Assistance Program (NAP) that use crop yield damage thresholds. Disaster payment triggers for floods and excess moisture rely directly on the extent of crop damage. Federal insurance indemnities and disaster aid payments partially offset the income losses generated through the biophysical channel. The institutional responses are conditional and activate only when program-specific thresholds are exceeded.

The two parallel specifications employed in this paper have different interactions with the two pathways. The Palmer Z-index is primarily a moisture anomaly index and operates through both pathways. Composite drought indices or moisture anomaly indices of this kind are closely related to the inputs underlying the U.S. Drought Monitor which is in turn used by the USDA for drought assistance programs. The Palmer Z-index is regularly used to monitor rapidly developing drought conditions. The high temperature bins on the other hand capture a dimension the Z-index does not. Severe heat days with average temperature above 30 degrees Celsius operate through the biophysical pathway, are potent and trigger physiological damage that reduce yields (Schlenker and Roberts, 2009). However, the institutional response to heat is comparatively muted. While it is true that high temperatures accelerate evapotranspiration and depletion of soil moisture, they are not perfect predictors of crop insurance or disaster payments. They are however, better predictors of thermal stress - something that the drought indices are not too good in predicting. The moderate correlation between extreme heat days and moderate to extreme drought pentads (Figure 6.2) confirms the fact that the two stressors occur together frequently but are far from identical. This leaves a substantial share of thermal stress events unaccompanied by drought designation and therefore outside of the institutional response pathway.

Chapter 2

Literature Review

This study contributes to the literature in several ways. First, it investigates both ends of the Palmer Z-index, corresponding to drought and flood conditions, providing a direct comparison of both hazards. It also investigates multiple temperature bins. Second, it investigates how these hazards drive insurance payments, shedding light on the channels through which farm income measures are affected. These contribute to the literature on climate and farm economy, agricultural adaptation and resilience to disasters, crop insurance and natural hazards.

Drought events present multifaceted challenges to researchers – it not only poses a challenge to the agricultural economy and the environment but also to researchers as to how they should define it. Wilhite and Glantz (1985) term droughts as ‘creeping phenomena’ whose onset and termination are notoriously difficult to predict. This characterization was originally coined by Gillette (1950) due to the intrinsic nature of droughts – gradual accumulation driven by precipitation deficits. Tannehill (1947) articulated this phenomenon by stating that the impact of a drought only becomes apparent in retrospect – we only truly know its significance when crops have withered and died.

Even though there are challenges to defining a drought event, droughts have profound significance for empirical research. Mishra and Singh (2010) emphasize that droughts occur in virtually all climatic zones and are primarily associated with precipitation reductions over extended periods. However, factors like temperature, wind, humidity, and the timing and intensity of rainfall all determine the eventual severity of the drought event. Wilhite and Glantz (1985) state that a given precipitation deficit might lead to a severe drought in one region but might pass unnoticed in another due to differences in water demand, cropping system and infrastructure. This has led to drought events being defined in multiple ways that each emphasize a different dimension – meteorological, hydrological, agricultural or socioeconomic.

Despite the presence of definitional and conceptual challenges, the economic importance of drought events is unambiguous. Between 1980 and 2003, droughts and associated heat waves were responsible for 41.2 percent of estimated disaster-related costs which amounted to \$144 billion (Ross and Lott, 2003). Agriculture is one of the primary affected sectors. Crop failure, reduced productivity and livestock losses directly lead to the loss of farm income reductions and ultimately affects the entire rural economy. Therefore, as climate change intensifies the global hydrologic cycle which leads to more of these extreme events, it is of utmost importance to understand the magnitude and mechanism of these agricultural impacts for effective policy design (Milly et al., 2002).

A significant step towards a unifying drought classification scheme came with the development of the U.S. drought monitor (USDM) in 1999. The USDM incorporates and synthesizes multiple indicators used to gauge the severity of drought events – it is a composite index. It uses six key parameters – the Palmer Drought Severity Index (PDSI), CPC Soil Moisture Model (percentiles), USGS Daily Streamflow (percentiles), Percent of Normal Precipitation, Standardized Precipitation Index (SPI), and a remotely sensed Satellite Vegetation Health Index (Svoboda et al., 2002). Apart from these six, it also depends on a set of supplementary indicator inputs from a panel of experts. It ranges from D0 (Abnormally Dry) to D4 (Exceptional Drought).

Kuwayama et al. (2019) provided empirical evidence that the USDM classification has correlation with agricultural outcomes. They studied the impact of drought classified using the USDM categorization on yield and farm income measures for the continental U.S. and found that drought reduces both corn and soybean yields but does not have significant impact on farm income measures. The use of the USDM categorization is seen in several major drought management decisions, especially by the USDA. A county is designated to be in drought by the USDA when it faces a USDM D2 level drought for eight consecutive weeks or D3/D4 for any period of time during the growing season (USDA, 2015). However, the USDM drought categorization includes a vegetation health indicator which raises concerns about endogeneity where agricultural outcomes themselves influence drought classification (Kuwayama et al., 2019). This endogeneity concern has led us to use the Palmer Z-index instead, which is not only free from these concerns but is also a good indicator of short-term droughts and moisture anomalies.

The Palmer Z-index is also known as the Palmer Moisture Anomaly Index. It was developed as a component of the broader Palmer Drought Index (PDI) system, which also includes the Palmer Drought Severity Index (PDSI) and the Palmer Hydrological Drought Index (PHDI) (Palmer, 1965). Unlike the PDSI and the PHDI which have long memory and are designed for long-term assessment of drought conditions (Guttman, 1998), the Palmer Z-index is designed to measure short-term moisture anomalies for a period such as a month or a week. The Z-index represents the difference between actual precipitation and the "climatologically appropriate for existing conditions" (CAFEC) precipitation weighted by a climate characteristic factor. The Z-index incorporates both temperature and precipitation data - the latter through the evapotranspiration term. The version of the Z-index used in this paper uses non-overlapping six pentad blocks of precipitation and potential ET. It uses reference evapotranspiration and precipitation from gridMET and a static soil water holding capacity layer from STATSGO. A full breakdown of the sub-monthly calculation is provided by Rhee and Carbone (2007).

There is a substantial body of research, that goes parallel to the drought literature, examining how temperature and precipitation affect crop yields using the 'degree day' approach. The takeaway from this body of research is that temperature effects are nonlinear as is seen from flexible specifications allowing temperature effects to vary across multiple degree bands and polynomial precipitation terms (Schlenker and Roberts, 2009; Burke and Emerick, 2016). This paper does not use temperature and precipitation controls as the Palmer Z-index is a composite index containing both, however, estimates from specifications including those controls are reported in the appendix in the combined models. The effects of temperature and precipitation are explored in a parallel specification.

A central question in similar studies is related to the extent to which agricultural producers have adapted or can adapt to these climatic stresses. Schlenker and Roberts (2009) test for adaptation by splitting their sample into northern and southern states and into two periods but find no significant evidence of adaptation. They split the sample into two time periods of equal length but find no significant change in the critical temperature threshold for the two samples even though average yield in the more recent sample is about twice the former. Burke and Emerick (2016) come to a similar conclusion inferring limited adaptation using a long differences estimator - long-run adjustments appear to offset almost none or very little of the yield damages coming from temperatures above the critical threshold. This study does not directly align with these adaptation studies but indirectly contributes to it by investigating asymmetries in temperature, drought and flood effects along dimensions that may reflect adaptive capacity.

Chapter 3

Data and Empirical Strategy

3.1 Data

The study uses multiple sources of county-level agricultural, weather, hazard and economic data to construct an unbalanced panel dataset consisting of farm net income receipts, agricultural yields, field crop acreage, flood hazard events, Palmer Z-index, insurance payments, temperature and precipitation.

The sample includes 889 counties from 11 Midwestern states – Illinois, Indiana, Iowa, Kansas, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota and Wisconsin. These states have been chosen because they account for a substantial national share of corn and soybean production. Some counties have been dropped due to missing data or singletons. The data is annually observed from 2002 to 2023. Census data is from the USDA census years 2002, 2007, 2012, 2017 and 2022.

The agricultural production and acreage data come from the USDA National Agricultural Statistics Service (NASS) surveys. The net farm income data come from the USDA census data and are available for the census years 2002, 2007, 2012, 2017 and 2022. The insurance payments data coming from the USDA census datasets are available for 2007, 2012, 2017 and 2022. The crop and livestock insurance payment is defined as all crop and livestock insurance payments received excluding payments from casualty insurance, vehicle liability, blanket policies and operator dwelling insurance (USDA NASS, 2019). In addition, crop insurance indemnity payments data from the USDA Risk Management Agency have also been used, which contains insurance payments for all crops and also payments disaggregated by crop type. Disaggregated insurance payment data for corn and soybean are used in conjunction with the census data for the years 2007, 2012, 2017 and 2022.

The income measure focused on is the net farm income of operations. The net cash farm income of operations is defined as the cash amount arrived at by subtracting total farm expenses from total sales, government payments and other farm-related income. The net farm income of operations includes the value of commodities produced under production contract by contract growers. Similarly, the net cash farm income of producers is their total revenue which includes fees for producing under a production contract, total sales not under a production contract, government payments and farm related income, subtracted by total expenses paid (USDA NASS, 2019). The results for net producers income is provided in appendix A.8.

Flood event data is taken from the National Oceanic and Atmospheric Administration (NOAA) Storm Events Database for the growing season. The growing season is defined June 1st to September 30th. The Palmer Z-index data is taken from the gridmet datasets provided by The Climatology Lab (Abatzoglou, 2013). The data are reported every 5 days (Pentad) and have a resolution of approximately 4 kilometers. Daily minimum and maximum temperature data and daily precipitation data were obtained from the PRISM gridded climate dataset at a 4 kilometer resolution at each county centroid from 2002 to 2023. Daily mean temperature is constructed as the midpoint between the maximum and minimum daily temperature and that is used to construct county-year-day counts within six 5 degrees Celsius bins (below 10 degrees Celsius through 30+ degrees Celsius) for the June to September growing season. Daily precipitation is summed and averaged over the growing season to calculate average daily precipitation in the growing season and its squared value. This process for temperature and precipitation data is repeated for the planting season (April to May) and the extended season (January to September).

The Palmer Z index (Palmer, 1965), originally a monthly measure of moisture anomaly, captures the departure of actual precipitation from the climatically appropriate precipitation for a given location. It is formally formulated as $Z = dK$, where $d = P - \hat{P}$ is the difference between the actual precipitation and the CAFEC (Climatically Appropriate For Existing Conditions) precipitation and K is a weighting factor that adjusts for the moisture departure at the locality. The CAFEC precipitation $\hat{P}$ is derived from a hydrologic accounting procedure which incorporates potential evapotranspiration, soil moisture recharge, runoff, and soil moisture loss. Each of these is weighted by empirically derived climatic coefficients. Therefore, the index reflects not just rainfall shortfalls but departures from the full moisture balance appropriate to the prevailing climate. The Z index values are dimensionless and cannot be interpreted as inches of moisture departure directly. Each value of the index expresses the degree to which the moisture aspect of the weather for that pentad deviated from the average moisture climate of that location and season. Both the Palmer Drought Severity Index (PDSI) and the Palmer Z-index are derived from the Palmer model. However, the Palmer Z-index is much more likely to contain better estimates of agricultural moisture shortages, is much more responsive to short-term moisture deficiencies and is less sensitive to change in calibration periods (Karl, 1986). The Palmer Z-index is much more suited to this study than the PDSI, as this paper aims to assess the within-season effects of hydrometeorological hazards on agricultural outcomes.

3.2 Summary Statistics and TWFE Variance Decomposition

Table 3.1: Summary Statistics and Two-Way Fixed Effects Variation Decomposition — Outcomes

	Overall		SD		
Variable	Mean	SD	Within	Between	N
Corn Yield (Bu/Acre)	152.555	36.234	–	–	16,920
Soy Yield (Bu/Acre)	45.539	10.862	–	–	16,768
Log Corn Yield (Log Bu/Acre)	4.991	0.292	0.165	0.197	16,920
Log Soy Yield (Log Bu/Acre)	3.784	0.278	0.152	0.194	16,768
Operations Income ($M)	46.711	49.704	22.119	38.820	4,118
Producers Income ($M)	40.067	41.697	18.048	32.921	4,117
Ops Income/Acre ($/acre)	303.786	632.763	488.071	378.709	4,083
Prod Income/Acre ($/acre)	254.256	514.855	411.242	290.461	4,082
Census Insurance ($M)	2.717	4.695	3.238	2.719	3,100
RMA Total Indemnity ($M)	6.252	12.102	8.646	6.357	3,227
RMA Corn Indemnity ($M)	4.530	10.258	7.403	5.054	3,154
RMA Soy Indemnity ($M)	1.313	2.576	1.837	1.604	3,138

Notes: Within SD measures variation within counties after removing county and year FE. Between SD measures variation across counties (weighted). Within and between SD are not reported for level yields (–) as these variables are not used in estimation. Income models use census years (2002, 2007, 2012, 2017, 2022). Census insurance and RMA indemnities use census years (2007, 2012, 2017, 2022).

Table 3.2: Summary Statistics and Two-Way Fixed Effects Variation Decomposition — Independent Variables

	Overall		SD		
Variable	Mean	SD	Within	Between	N
Palmer Z-Index (Pentads, Jun-Sep)					
Moderate to Extreme Drought ($Z < -3.0$)	1.906	3.852	2.301	0.691	17,209
Mild Drought ($-3.0 \leq Z < -2.0$)	2.712	3.056	2.654	0.608	17,209
Mild Wet ($2.0 \leq Z < 3.0$)	1.805	2.099	1.888	0.400	17,209
Moderate to Extreme Wet ($Z \geq 3.0$)	2.045	3.108	2.699	0.541	17,209
Total Floods (Growing Season)	0.897	1.996	1.742	0.827	17,515
Temperature Bins (Days per 5°C, Jun-Sep)					
Below 10°C	1.180	1.978	1.091	1.417	17,493
10-15°C	7.808	6.233	2.846	5.020	17,493
15-20°C (Reference)	31.386	14.077	5.124	11.476	17,493
20-25°C	54.697	10.991	7.027	6.741	17,493
25-30°C	25.499	17.132	5.286	14.414	17,493
30°C+	1.431	3.736	2.424	2.382	17,493
Precipitation (Jun-Sep)					
Mean Precipitation (mm/day)	3.230	1.069	0.835	0.406	17,493
Mean Precipitation Sq	11.578	7.968	6.403	2.823	17,493

Notes: Within SD measures variation within counties after removing county and year FE. Between SD measures variation across counties (weighted). N = observations.

Table 3.1 presents summary statistics and the two-way fixed effects variance decomposition for all outcome and independent variables, computed from the sample used in the econometric analysis. The within standard deviation is the year-to-year variation within counties after demeaning the fixed effects and it serves as the source of identifying variation in the two-way fixed effects estimator. The between standard deviation on the other hand, captures persistent cross-county differences absorbed by county fixed effects.

The yield outcomes show a near even split between the within and between SDs. Log corn yield has a within standard deviation of 0.165 against a between of 0.197 and log soy yield follows a similar pattern - 0.152 versus 0.194. This confirms that approximately 32% of the the total yield variation is temporal. The income level variables are dominated by between-variation. Operations income has a within SD of $22.1 million USD against a between SD of $38.8 million USD. This means that most of the income variation comes from persistent cross-county difference in farm scale and productivity rather than within-county year-to-year fluctuations. The county fixed effect absorbs this cross-county variation. The per-acre income variables show opposite patterns. The within standard deviations exceed between standard deviations by roughly 30% - dividing by income accounts for the relatively persistent scale effects that vary across counties. However, the per-acre income variables are highly dispersed relative to their means. This likely reflects many outlier counties with very small planted acreage producing implausibly large per-acre values. So the resulting estimates for the per-acre models should be interpreted with caution. The insurance outcomes are dominated by within variation. RMA total indemnities have a within standard deviation of 8.6 million USD against between standard deviation of 6.4 million USD. Another point to note is that 2012 was a catastrophic drought year, among the four census years used here, so that drives the mean more than other years (Figure 6.1).

All the Palmer Z-index variables are strongly within variation dominated. The within standard deviations are three to four times larger than the between standard deviations. Moderate to extreme drought has a within standard deviation of 2.3 pentads against between standard deviation of 0.69 pentads. This implies that approximately 92% of moderate to extreme drought variance is temporal. This shows that the moisture conditions that we are associating with droughts are predominantly year to year phenomena within counties. This makes them a good fit for the two-way fixed effects models. The temperature bins show that cold and moderate bins are between dominated and the extreme heat bin above 30 degrees Celsius has almost equal within and between standard deviations despite a mean of only 1.43 days per season. The combination of a low mean value and a high within variance makes year to year fluctuations in this bin the primary source of identification. Lastly, precipitation is within dominated which is consistent with year to year rainfall variability.

The frequency distributions (Figures 3.1 and 3.2) shows that moderate to extreme drought and the 30+ temperature bin are the rarest conditions, with zero exposure recorded in 64.2 and 70.7 percent of county-year observations respectively. Mild drought is the most common - present in 64.4% of the county-years. Mild and moderate to extreme wet categories fall in between them. Among the temperature bins, the 15-20 and 20-25 degree bins are present in every county-year. The 30+ degrees bin follows a similar episodic pattern as the Palmer moderate to extreme drought category - only 29.3% county-year observations.

Figures 3.3 and 3.4 show the cumulative geographic distribution of all the independent variables in the study area across 2002 to 2023. The maps show clear concentrations of moderate to extreme drought and wet conditions. The western and central corn belt shows more drought concentrations and the northern and eastern belt shows more concentration of wet conditions. The severe heat bin of 30+ degrees is more concentrated in the southwestern counties.

Overall, it can be seen that the TWFE models chosen are good picks for this dataset. There is sufficient within-county temporal variation for precise identification for the variables while they remain plausibly exogenous to farm-level decisions conditional on the fixed effects.

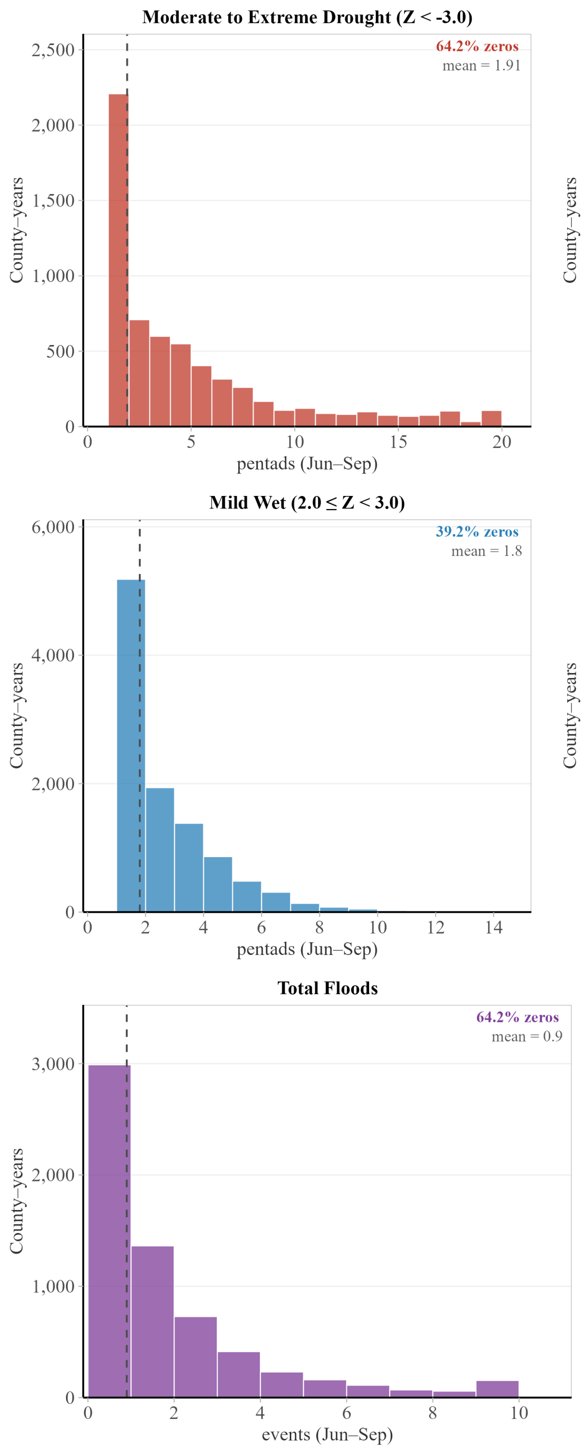

Figure 3.1: Frequency Distribution of Growing Season Palmer Z-Index Categories and Flood Events

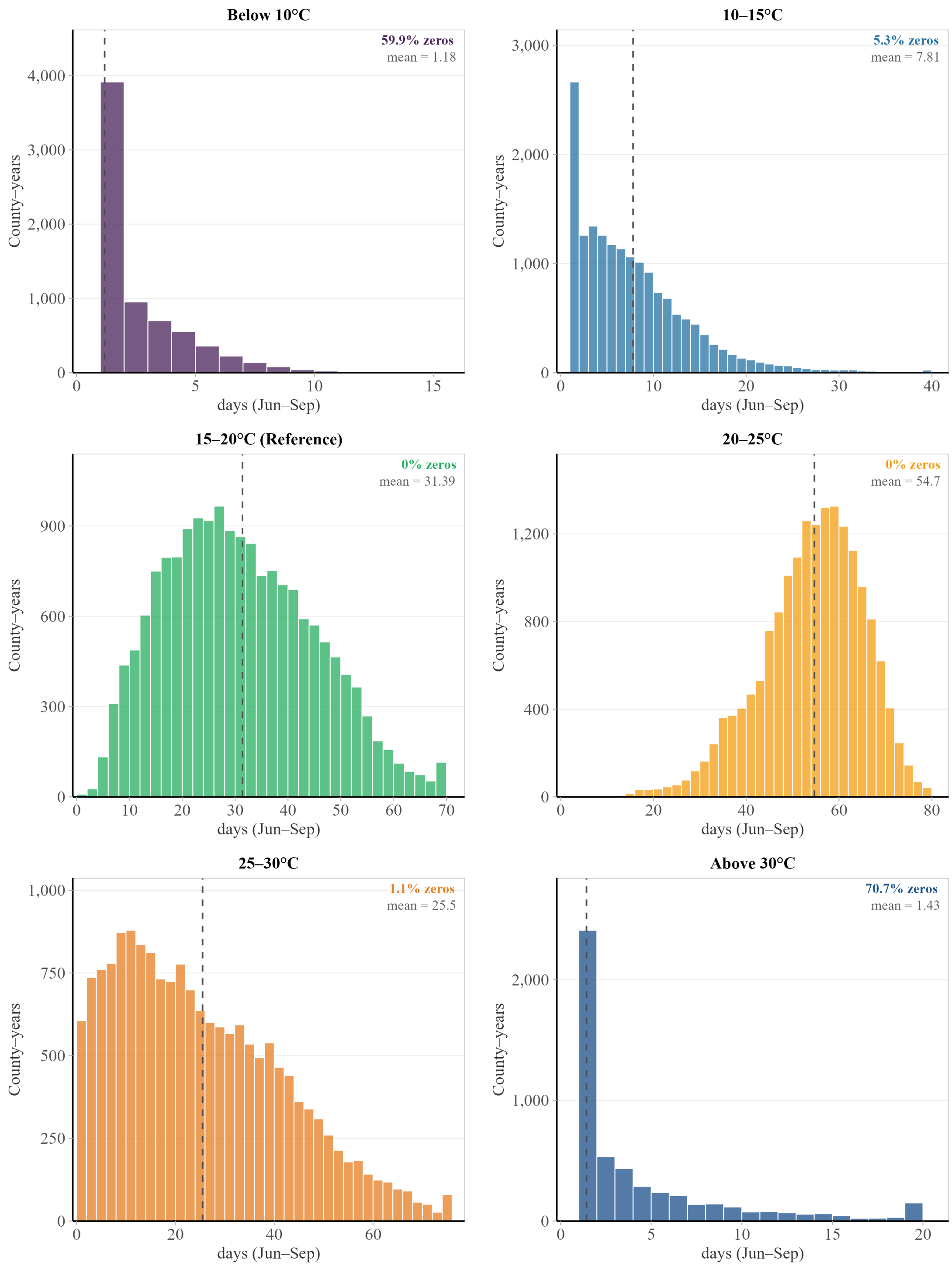

Figure 3.2: Frequency Distribution of Growing Season Temperature Bins

Table 3.3: Frequency Distribution of Moisture/Weather Variables (2002-2023)

Variable	Positives (%)	Mean	SD	Min	Median	Max
Palmer Z-Index (Pentads per Growing Season)						
Moderate to Extreme Drought ($Z < -3.0$)	35.8%	1.906	3.852	0	0	24
Mild Drought ($-3.0 \leq Z < -2.0$)	64.4%	2.712	3.056	0	2	18
Mild Wet ($2.0 \leq Z < 3.0$)	60.8%	1.805	2.099	0	1	15
Moderate to Extreme Wet ($Z \geq 3.0$)	45.9%	2.045	3.108	0	0	24
Total Floods (Growing Season)	35.8%	0.897	1.996	0	0	49
Temperature Bins (Days per Growing Season, Jun-Sep)						
Below 10°C	40.1%	1.180	1.978	0	0	17
10-15°C	94.7%	7.808	6.233	0	7	52
15-20°C (Reference)	100%	31.386	14.077	1	30	77
20-25°C	100%	54.697	10.991	11	56	82
25-30°C	98.9%	25.499	17.132	0	23	92
30°C+	29.3%	1.431	3.736	0	0	52
Precipitation (Jun-Sep)						
Mean Precipitation (mm/day)	100%	3.230	1.069	0.296	3.087	9.563

Notes: Positives = percentage of county-year observations with non-zero values. N = 17,493 for temperature and precipitation; N = 17,209 for Palmer Z-index; N = 17,515 for floods.

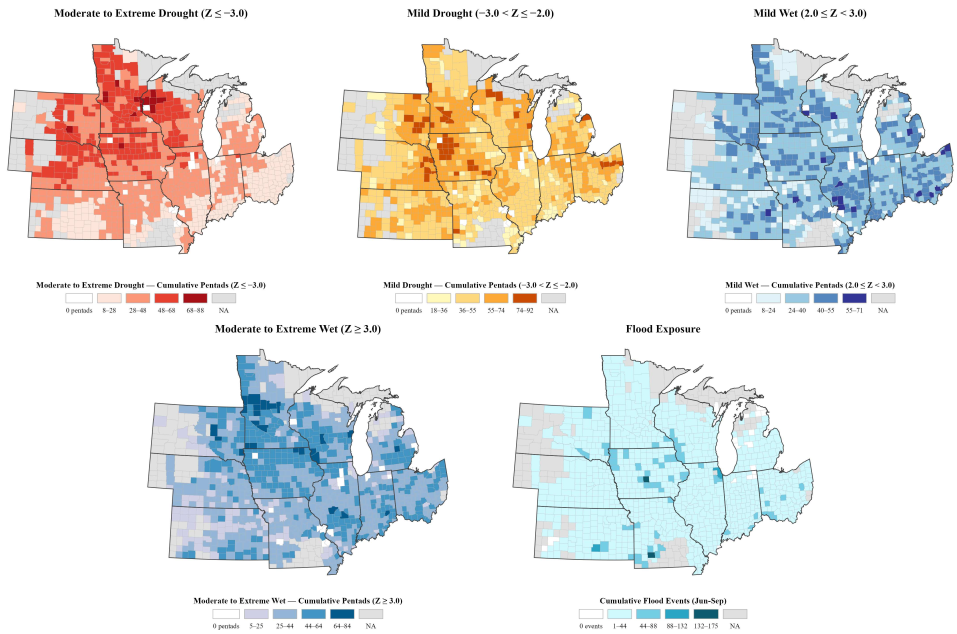

Figure 3.3: Moderate to Extreme Drought, Mild Drought, Mild Wet, Moderate to Extreme Wet and Flood Events in the U.S. Midwest (2002-2023)

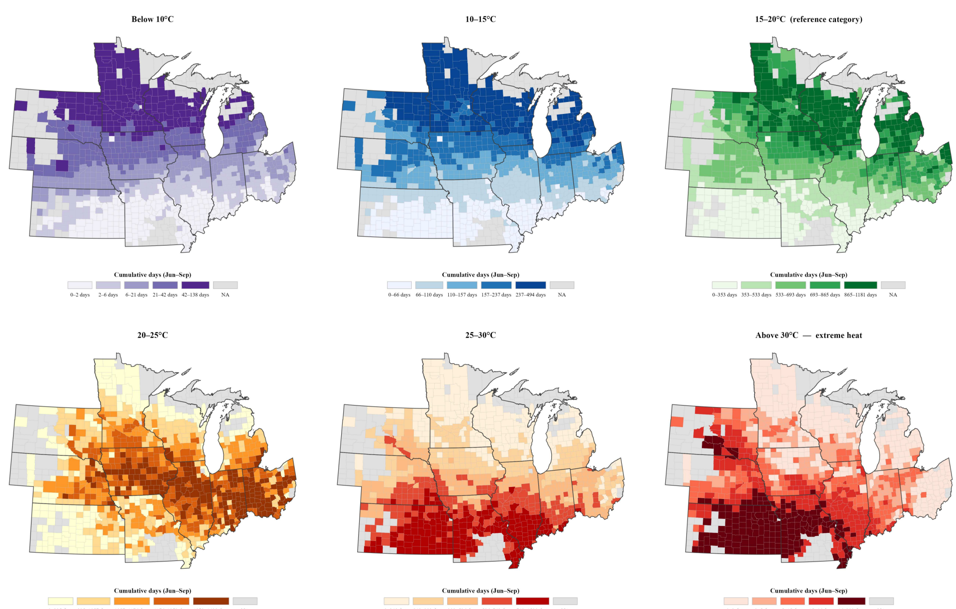

Figure 3.4: Cumulative Distribution of Temperature Bins across the U.S. Midwest (2002-2023)

Chapter 4

Specifications

4.1 Palmer Z-index Model Specification

A fixed-effects regression framework is employed to estimate the associations between extreme moisture conditions and agricultural outcomes. The empirical specification takes the following general form:

$$\begin{aligned} Y_{ct} = {} & \beta_1 \text{ModerateToExtremeDrought}_{ct} + \beta_2 \text{MildDrought}_{ct} + \beta_3 \text{MildWet}_{ct} \\ & + \beta_4 \text{ModerateToExtremeWet}_{ct} + \beta_5 \text{FloodCount}_{ct} + \alpha_c + \gamma_t + \varepsilon_{ct} \end{aligned} \tag{4.1}$$

where Y_{ct} represents the outcome variable for county c in year t. Separate regressions have been estimated for seven outcome variables: log corn yield, log soybean yield, net operations income (in millions of dollars), net producers income (in millions of dollars), net operations income per acre, net producers income per acre and total insurance receipts (in millions of dollars). Only the yield variables have been logged. The net income variables have not been logged because of existing negative income values. The insurance payments have not been logged in order to keep them comparable to the income estimates. The Palmer Z-index is preferred over the Palmer Drought Severity Index (PDSI) for within-season analysis because the PDSI is designed for longer-term analysis that might conflate current conditions with antecedent history.

The Palmer Z-Index is a moisture anomaly index that incorporates both precipitation and temperature data. For each county-year observation, the Z-index is averaged over the June-September growing season and categorized into four binary bins: moderate to extreme drought ($Z \leq -3.0$), mild drought ($-3.0 < Z \leq -2.0$), mild wet ($2.0 \leq Z < 3.0$), and moderate to extreme wet ($Z \geq 3.0$). An additional control variable, FloodCount_{ct}, measures the number of flood events occurring during the growing season.

All of the specifications include county fixed effects (α_c) to control for time-invariant unobserved heterogeneity across counties, such as soil quality, topography, and long-term climate norms. Year fixed effects (γ_t) are included to absorb common time shocks affecting all counties. This could include national commodity prices, technological change, macroeconomic conditions etc. The standard errors are clustered at the county level to account for within-county serial correlation over time.

The analysis is conducted on three distinct samples. The sample sizes reported here are from the regression output. First, the yield models use a panel of up to 16,896 county-year observations for corn (887 counties) and 16,740 for soybeans (883 counties), spanning from 2002 to 2023 after accounting for missing data. Second, the income models are restricted to census years (2002, 2007, 2012, 2017, and 2022), yielding 4,113 observations across 889 counties after accounting for data suppression for operations income. Third, the insurance models are further restricted to years with available insurance receipts data (2007, 2012, 2017, and 2022), resulting in 3,077 to 3,222 observations across 854 to 888 counties depending on the insurance outcome.

In order to determine an appropriate cutoff distance or spatial bandwidth for the Conley correction procedure, within-year spatial correlograms are estimated for all twenty primary models. For each model and year, mean pairwise products of standardized and demeaned residuals are computed across all county pairs. These are then sorted into 50 kilometer distance bands and then averaged across years. This within-year approach is appropriate for two-way fixed effects models because the year fixed effects remove aggregate annual shocks and leave within-year cross-sectional correlation. The natural cutoff is taken to be the first distance band at which the 95 percent confidence interval for mean pairwise correlation includes zero. Since cutoffs vary across outcome types, a conservative rule of taking the largest natural cutoff among the primary yield and income models is adopted. After rounding up to the nearest 50 kilometers, this yields a bandwidth of 425 kilometers - midpoint of the 400-450 kilometer band. The standard error inflation relative to county clustering increases with bandwidth and flattens near and the beyond the natural cutoff as additional pairs contribute near-zero correlation.

The Conley standard errors approach was chosen after careful evaluation of the Moran's I values for each regression model. The maximum Moran's I value was 0.19, indicating moderate spatial correlation and warranting the need for spatial correlation robust standard errors but not a fully spatial model. The yield models were the ones with the highest spatial correlation. A within-year spatial correlation analysis was conducted. For each year in the estimation sample, pairwise residual correlations were computed across all county pairs as a function of geographic distance and then averaged across years. The optimal cutoff was seen to be 425 kilometers - the midpoint of the first 50 km band whose 95% confidence interval includes zero.

4.2 Temperature-precipitation Model Specification

To examine the differential effects of temperature extremes and precipitation across the growing season, a flexible temperature bin model is used. Temperature bins have been previously used by Schlenker and Roberts (2009). Miao et al. (2016) have also used temperature bins but those corresponded to growing degree days and overheat degree days. This approach allows for non-linear temperature effects by applying discretization of the temperature distribution into 5 degrees Celsius intervals. The model is specified as:

$$\begin{aligned} Y_{ct} = \beta_1 \text{TempBelow10}_{ct} + \beta_2 \text{Temp10to15}_{ct} + \beta_3 \text{Temp20to25}_{ct} \\ + \beta_4 \text{Temp25to30}_{ct} + \beta_5 \text{TempAbove30}_{ct} + \beta_6 \text{Precip}_{ct} \\ + \beta_7 \text{PrecipSq}_{ct} + \alpha_c + \gamma_t + \varepsilon_{ct} \end{aligned} \tag{4.2}$$

where Y_{ct} denotes the outcome variable for county c in year t (log corn yield, log soybean yield, net farm income, or insurance receipts). The temperature variables measure the number of days in each 5 degrees Celsius bin during the growing season (June-September). Days with mean temperature between 15-20 degrees Celsius serve as the omitted reference category. Assuming a more symmetric relationship between precipitation and the outcome variables, especially yields, a mean precipitation and its square term is used to capture potentially nonlinear effects of moisture.

The precipitation coefficients (β_6, β_7) captures both water deficit and excess precipitation effects. The specification includes county fixed effects (α_c) and year fixed effects (γ_t).

The temperature bin specification offers several advantages over simpler measures such as growing degree days (GDD) or average temperature. Firstly, it captures the non-monotonic nature of the marginal effects of temperature. Secondly, it is able to identify specific temperature ranges considered critical for plant growth. Thirdly, it is more transparent and easier to interpret than higher order polynomial terms. The coefficients of the temperature bins are marginal effects relative to the reference category.

4.2.1 Empirical Objective and Identification

The specifications are designed to estimate the average association of moderate to extreme drought, mild drought, moderate to extreme wet and mild wet conditions, as measured by the Palmer Z-index bins, along with flood counts and multiple temperature bins in 5 degrees Celsius intervals during June to September with corn and soybean yields, net farm cash income and insurance payment receipts. The identification comes entirely from within-county year-to-year variation in weather exposure after accounting for the common annual trends.

The conceptual framework provided in figure 1.1 broadly motivates the empirical strategy of this paper. Since the two pathways described potentially offset each other, a yield loss that depresses revenue may be partially compensated by indemnity payments and hence the net effect of a given hazard cannot be inferred from yield impacts alone. Therefore, the empirical goal of this paper is estimate the effect of the specified hazards at each node of the framework - on yields, on net income and on insurance transfers. In that regard, the approach is to exploit the spatial and temporal variation in average daily temperature, drought and flood exposure to investigate their impacts on crop yield and farm income. The two-way fixed effects design - with county and year fixed effects - is implemented on the unbalanced panel dataset, with both standard errors clustered at the county level and Conley standard errors robust to spatial autocorrelation with a cutoff of 425 kilometers.

Two parallel models have been estimated that not only help us understand different dimensions of the growing season weather stress but also help us understand the contrast between estimates from composite indices and raw weather variables. The Palmer Z-index is a moisture anomaly measure that integrates temperature, precipitation, and soil characteristics into a single index capable of identifying drought and excess moisture conditions. But, just like all drought indices, it is not precise in picking up all detrimental effects originating from extreme weather conditions like pure thermal stress. Therefore, each specification has its own strengths and weaknesses. The temperature-bin approach provides a more granular measure of temperature effects but misses the interaction between temperature, precipitation and soil conditions. Therefore, rather than choosing one approach this study has employed both, which helps leveraging their complementary strengths. The raw temperature-precipitation models identify the direct and specific heat and moisture exposure effects, while the Palmer Z-index models capture the compounded effect of temperature, precipitation and soil conditions. Agreement between the models gives us stronger evidence for hazard and extreme weather shocks, and divergence between the two provides guidance on where measurement choices matter for inference.

The central identifying assumption here is that after conditioning on county and year fixed effects, the remaining within county year to year variation in the growing season weather and hazard shocks is uncorrelated with other determinants of the outcome variables. This is a credible assumption because weather is not determined by farm-level decisions, input choices or technology adoption. It is completely determined by atmospheric processes.

One threat to identification is time-varying county-level factors such as improved farming practices, using improved seed varieties, expansion of irrigation capacity or basically any form of adaptation. These could be correlated with within-county weather variation over the entire panel. This source of bias cannot be entirely ruled out but it is worth noting that within-county adaptation decisions are unlikely to be driven by year-to-year deviations from county norms. That is the identifying variation exploited here. However, this paper takes a conservative stance and treats the estimates as reduced-form associations.

Chapter 5

Results

5.1 Yield and Net Farm Income Models for the Palmer Z-index

Table 5.1 presents the Palmer Z-index yield and income regression model (equation 4.1) results with both county clustered and Conley standard errors at 425Km cutoff. The coefficients can be interpreted as percentage changes as the dependent variables are log-transformed yields. Significance stars correspond to the Conley standard errors.

Table 5.1: Palmer Z-Index: Yield and Operations Income Regressions

	Yield		Income ($M)
	Log Corn	Log Soy	Operations
Moderate to Extreme Drought	-0.0226^{***}	-0.0197^{***}	-0.3421
	(0.0010)	(0.0008)	(0.1130)
	[0.0040]	[0.0021]	[0.3003]
Mild Drought	-0.0104^{***}	-0.0114^{***}	0.4071
	(0.0006)	(0.0005)	(0.1535)
	[0.0020]	[0.0022]	[0.4023]
Mild Wet	-0.0009	0.0015	-0.7206
	(0.0006)	(0.0006)	(0.3504)
	[0.0014]	[0.0015]	[0.7094]
Moderate to Extreme Wet	-0.0075^{***}	-0.0036^{***}	-0.4018^{*}
	(0.0005)	(0.0004)	(0.2213)
	[0.0014]	[0.0010]	[0.1570]
Floods	0.0009	0.0001	0.2097
	(0.0008)	(0.0007)	(0.2725)
	[0.0018]	[0.0019]	[0.1631]
Observations	16,620	16,460	4,046
Counties	873	869	875
Years	22	22	5
Adj. R^2	0.710	0.730	0.748
Within R^2	0.134	0.141	0.009
RMSE	0.153	0.141	22.0

Notes: SE: () county, [] Conley (425 km).

Significance stars ($^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$) correspond to Conley SEs.

Both drought variables show statistically significant and robust negative associations with corn and soybean yields. For corn, each additional pentad in the moderate to extreme drought category corresponding to a Z-index value of less than -3, during the June-September growing season is associated with a 2.26% reduction in yield, while mild drought corresponding to a Z-index value between -3 and -2 is associated with a 1.04% reduction. The pattern is similar for soybeans, with moderate to extreme drought associated with a 1.97% reduction in yield and mild drought associated with a 1.14% reduction in yield.

Wet conditions also show negative associations with yields but these have smaller magnitudes. Moderate to extreme wet conditions corresponding to Z-index values greater than 3 are associated with yield reductions of 0.75% for corn and 0.36% for soybeans. Mild wet conditions corresponding to Z-index values between 2 and 3 show no robust statistically significant association with yields.

Total flood count shows no statistically significant association with either crop yield. This indicates that there is no statistical evidence that the frequency of reported flood events during the growing season affects yield outcomes after controlling for the Palmer Z-index moisture conditions.

Tables A.22 and A.23 show that the combined model with the drought index, the temperature and precipitation variables in the specification attenuates the estimates, as expected. For yields, the severe drought coefficient for corn falls from -2.26% to -1.25% and from -1.97% to -0.86% for soy. The estimates for temperature bins remain significant and show negative associations with both corn and soybean yield.

These results show that moderate to extreme droughts are the greatest threat to corn and soybean yields among all the extreme moisture condition categories constructed from the Palmer Z-index. The effects of moderate to extreme drought are approximately twice as large as mild drought and moderate to extreme wet conditions.

The net farm income level regression models show robust significant negative associations of the moderate to extreme wet category with both operations income and producers' income. Each pentad of moderate to extreme wet conditions is associated with reductions of \$0.4 million for operations income and \$0.24 million for producers income.

The mild drought coefficients using the clustered standard errors exhibit an interesting finding. The mild drought variable shows positive associations with income levels for both operations and producers even though it shows negative associations with both yield variables. However, these are not robust to spatial correlation. The total flood count variable does not show any statistically significant association with any of the income outcomes.

5.2 Yield and Net Farm Income Models for the Temperature Bins

Table 5.2: Temperature Bin: Yield and Operations Income Regressions

	Yield		Income ($M)
	Log Corn	Log Soy	Operations
Below 10°C	-0.0008	0.0017	-1.9074^{**}
	(0.0012)	(0.0012)	(0.4510)
	$[0.0054]$	$[0.0044]$	$[0.6466]$
10-15°C	-0.0021^{*}	-0.0041^{*}	-0.6852^{*}
	(0.0004)	(0.0006)	(0.1903)
	$[0.0009]$	$[0.0017]$	$[0.2759]$
20-25°C	0.0002	-0.0008	0.1324
	(0.0002)	(0.0002)	(0.0933)
	$[0.0007]$	$[0.0007]$	$[0.1429]$
25-30°C	-0.0059^{***}	-0.0058^{***}	-0.5770^{*}
	(0.0004)	(0.0004)	(0.1312)
	$[0.0014]$	$[0.0009]$	$[0.2279]$
30+°C	-0.0313^{***}	-0.0268^{***}	-2.0550^{***}
	(0.0015)	(0.0011)	(0.2054)
	$[0.0054]$	$[0.0011]$	$[0.4883]$
Precipitation (mm)	0.0996^{***}	0.1341^{***}	-9.7236^{**}
	(0.0081)	(0.0061)	(2.0335)
	$[0.0280]$	$[0.0157]$	$[3.2513]$
Precipitation Sq	-0.0124^{***}	-0.0149^{***}	1.0157^{*}
	(0.0011)	(0.0008)	(0.2875)
	$[0.0035]$	$[0.0021]$	$[0.4542]$
Observations	16,896	16,740	4,113
Counties	887	883	889
Years	22	22	5
Adj. R^2	0.746	0.770	0.763
Within R^2	0.243	0.270	0.065
RMSE	0.143	0.130	21.4

Notes: Reference category: 15-20°C. SE: () county, [] Conley (425 km).
Significance stars ($^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$) correspond to Conley SEs.

Table 5.2 shows the yield and net farm income regression results using the temperature bin specifications (equation 4.2) and both county clustered standard errors and Conley spatial HAC standard errors. The highest two temperature bins show robust statistically significant negative associations with yield - approximately 3.1% reduction per day above 30 degrees Celsius for corn and approximately 2.68% reduction in soybean yield compared to the reference category. Each day in in the 25-30 degrees bracket is associated with approximately 0.59% reduction in corn yield and 0.58% reduction in Soy yield.

The precipitation variables show an inverted-U relationship for both crops. The linear term coefficient is positive and the quadratic term coefficient is negative. This implies that yields increase with mean daily precipitation up to an optimal level but decrease after that point. This shows that mild precipitation is ideal for yields for both crops. The estimated turning points are 4.02 mm per day (490 mm per 122-day season) for corn and 4.49 mm per day (548 mm per season) for soybeans (Figure 5.1). At these optima, corn yield is predicted to be 22% higher than baseline and soy yield is 35% higher than baseline. These results are robust.

The highest temperature bin shows strong robust negative associations with both operations and producer income. A marginal increase in the number of days in the 30+ degrees Celsius bin with respect to the 15-20 degrees Celsius bin decreases operations income by approximately \$2.055 million and producers income by approximately \$1.98 million. Similarly, all other temperature bins except for the 20-25 degrees bin show negative significant associations with both income variables with respect to the reference bin. Precipitation shows a u-shaped relationship with both income variables. This implies that both low and high precipitation values are associated with better income outcomes. This suggests that both high and low mean daily precipitation values might be triggering price or insurance mechanisms. The minima are 4.79 mm/day for operations (584mm per season) income and 4.82 mm/day (588mm per season) for producers income. At these minima, the operations income variable is predicted to be \$23.3 million below baseline and the producers income variable \$20.6 million below baseline.These results are robust.

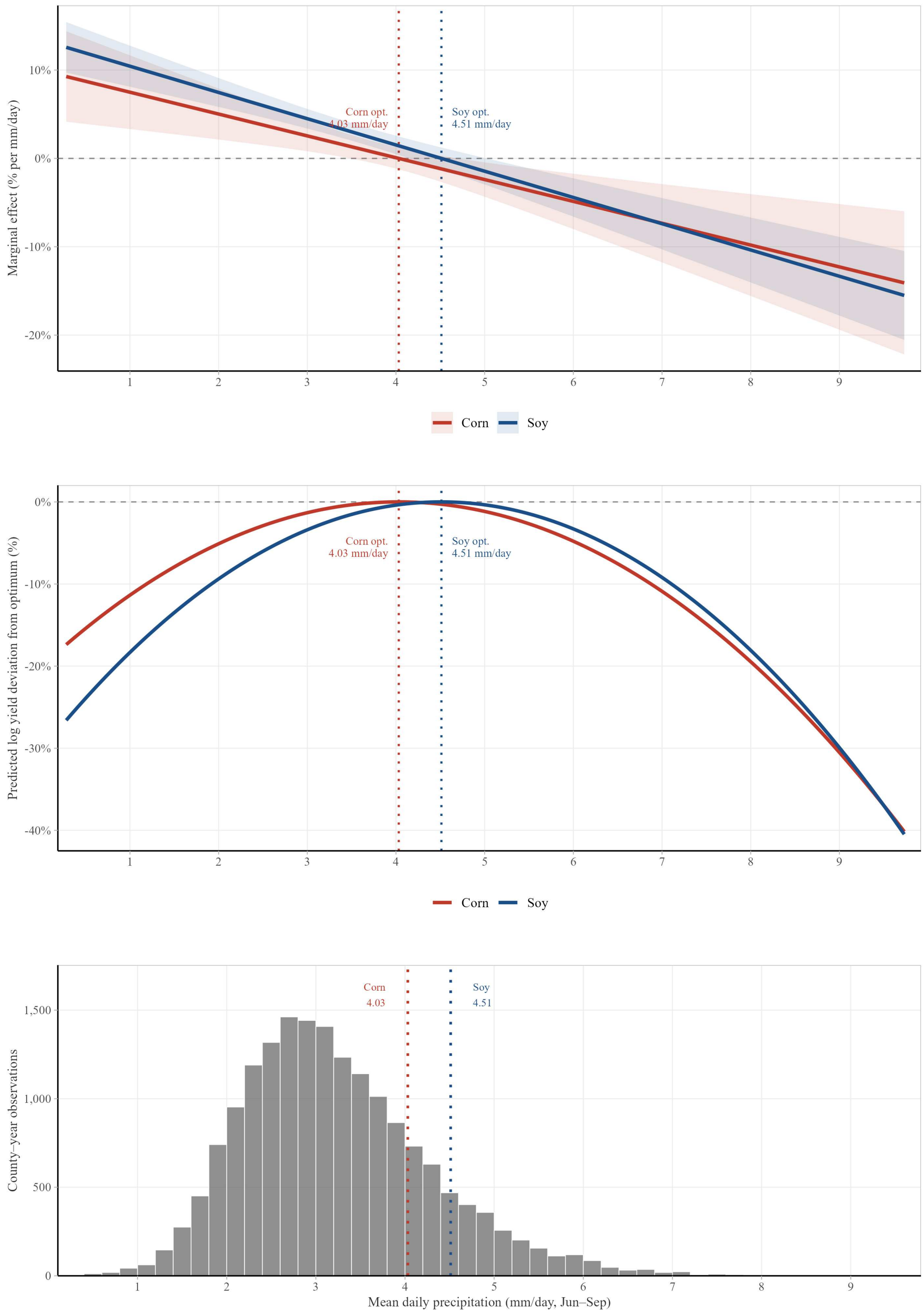

Figure 5.1: Marginal Effect and Inverted-U Relationship between Growing Season Average Daily Precipitation and Yields

The income results overall, reveal an interesting finding. Moderate to extreme drought conditions reduce crop yields and total income but on the other hand, mild drought conditions show a positive association with total income despite reducing yields. This result could be due to multiple reasons. For example, it could be possible if price compensation mechanisms are at play - if lower yields increase local prices or revenue per unit for non-affected producers. It could also be possible if insurance overcompensates for mild drought but undercompensates for moderate to extreme drought on average. Another possible explanation could be cross-crop portfolio effects or crop diversification effects - the agricultural economy of the U.S Midwest is not solely reliant on corn and soybean, and this mild drought window might be negatively associated with yields for corn and soy but not for other crops. Although this result is not robust to spatial correlation, it can be further investigated in future research to understand the role of prices and insurance mechanisms.

5.3 Insurance Receipt Models

Table 5.3 presents the regression results for the Palmer Z-index insurance receipts model (equation 4.1) for both types of standard errors.

Table 5.3: Palmer Z-Index: Insurance Regressions

	Insurance Receipts ($M)			
	USDA Census (All Crops)	RMA Total (All Crops)	RMA Corn	RMA Soy
Moderate to Extreme Drought	0.4133***	1.1407***	0.9029***	0.2248***
	(0.0283)	(0.0656)	(0.0556)	(0.0159)
	[0.0448]	[0.0900]	[0.1077]	[0.0520]
Mild Drought	−0.0619	−0.1625	−0.2527*	0.0612
	(0.0201)	(0.0546)	(0.0457)	(0.0151)
	[0.0449]	[0.1590]	[0.1157]	[0.0568]
Mild Wet	0.0668	0.3466	0.2691	0.0172
	(0.0523)	(0.1493)	(0.1364)	(0.0292)
	[0.1456]	[0.4306]	[0.3813]	[0.0726]
Moderate to Extreme Wet	0.1108	0.2679	0.1375	0.0588**
	(0.0334)	(0.0849)	(0.0707)	(0.0196)
	[0.0681]	[0.1763]	[0.1376]	[0.0221]
Floods	0.0604	0.1213	0.0209	0.0669
	(0.0570)	(0.1259)	(0.1099)	(0.0339)
	[0.1078]	[0.2355]	[0.2133]	[0.0606]
Observations	3,028	3,170	3,091	3,073
Counties	849	874	849	841
Years	4	4	4	4
Adj. R^2	0.427	0.396	0.377	0.388
Within R^2	0.131	0.145	0.132	0.125
RMSE	3.036	8.020	6.915	1.728

Notes: SE: () county, [] Conley (425 km). Significance stars: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table 5.4: Temperature Bin: Insurance Regressions

	Insurance Receipts ($M)			
	USDA Census (All Crops)	RMA Total (All Crops)	RMA Corn	RMA Soy
Below 10°C	0.0292	0.1084	0.0517	-0.0039
	(0.0666)	(0.1866)	(0.1701)	(0.0444)
	[0.0848]	[0.2112]	[0.1600]	[0.1006]
10-15°C	0.1262	0.2257	0.1421	0.0743^{*}
	(0.0277)	(0.0673)	(0.0582)	(0.0163)
	[0.0686]	[0.1273]	[0.1044]	[0.0366]
20-25°C	-0.0822^{**}	-0.3192^{***}	-0.2897^{***}	-0.0342
	(0.0149)	(0.0409)	(0.0364)	(0.0080)
	[0.0291]	[0.0933]	[0.0776]	[0.0334]
25-30°C	0.1291^{*}	0.3257^{***}	0.2035^{**}	0.0825^{*}
	(0.0269)	(0.0599)	(0.0524)	(0.0167)
	[0.0647]	[0.0925]	[0.0652]	[0.0345]
30+°C	0.2571	0.6316	0.3712	0.2283^{**}
	(0.0513)	(0.1204)	(0.1045)	(0.0334)
	[0.1990]	[0.5349]	[0.4741]	[0.0698]
Precipitation (mm)	-2.7655	-6.2714	-3.6285	-2.3900^{*}
	(0.5769)	(1.2874)	(1.0690)	(0.2990)
	[1.8873]	[5.0217]	[4.4943]	[0.9519]
Precipitation Sq	0.3983	0.9206	0.5377	0.3213^{*}
	(0.0886)	(0.1840)	(0.1502)	(0.0452)
	[0.2639]	[0.6394]	[0.5600]	[0.1440]
Observations	3,077	3,222	3,140	3,122
Counties	863	888	862	854
Years	4	4	4	4
Adj. R^2	0.436	0.414	0.376	0.466
Within R^2	0.146	0.172	0.131	0.238
RMSE	2.993	7.871	6.903	1.605

Notes: Reference category: 15-20°C.

SE: () county, [] Conley (425 km). Significance stars: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

The USDA census total insurance receipts outcome variable shows a strong positive association with moderate to extreme drought conditions. Each additional pentad of moderate to extreme drought during the June-September growing season is associated with an increase of $0.41 million in total insurance receipts. The moderate to extreme wet condition variable shows a robust positive association with the RMA Soy indemnities - each additional pentad is associated with an increase of $0.06 million. The moderate to extreme drought variable's positive association with all four insurance outcome variables is robust. One other robust association is between the mild drought variable and the RMA Corn variable. Mild drought is negatively associated with RMA corn indemnity payments. This is a notable result because previously it was seen that the mild drought variable has negative associations with both crop yields. The mild wet condition variable and total reported flood count variable show no statistically significant association with any insurance outcome. Table A.24 shows reductions in insurance payments after controlling for weather in the Palmer Z-index specification. For example, estimates for census insurance payment and RMA total indemnities are respectively $0.27 million and $0.78 million.

Table 5.4 presents the regression results for insurance receipts and indemnities using the 5 degrees temperature bins. As with the other models, the 15-20 degrees bin has been used as the reference category. The 30+ degrees bin shows positive associations with all insurance variables. These are consistent with the yield results where the 30+ bin showed the largest negative associations with yield. However, only the coefficient associated with the RMA Soy variable is robust. The 25-30 degrees bin shows robust positive associations with all the insurance variables but the magnitudes are approximately half of the 30+ degrees bin. It can be seen that the 10-15 degrees bins are also positively associated with all the insurance variables but only the RMA Soy coefficient is robust. The below 10 degrees Celsius bin shows no significant association with any of the insurance variables but this is almost certainly due to the rarity of these events in the dataset. The 20-25 degrees bin shows all negative significant associations with all the insurance variables and they are all robust. The intuition here is that this bin represents the optimal growing temperature window leading to maximized yields, minimal crop damage and hence minimum insurance claims. Lastly, the precipitation variable shows a U-shaped relationship here again but only robustly for the RMA Soy outcome variable. The turning point is at 3.72mm per day (453mm per season). This suggests that insurance payments increase for both low precipitation (droughts) and high precipitation (excess moisture/floods).

5.4 Combined Model Results

Appendix tables A.21, A.22 and A.23 report specifications that include both the Palmer Z-index categories and temperature bins jointly. The coefficient results provide qualitatively similar results to the separate models. For yields, moderate to extreme drought continues to show significant negative associations with corn and soy yields (-1.25% and -0.86% respectively) while the 30+ degrees Celsius bin continues to show the largest single association with yield loss for both crops (-2.73% corn, -2.37% soy). The income results show a sharp divergence by hazard. Drought categories are not significant predictors of operations or producer income with temperature bins are included except for a positive association of mild drought with producer income, whereas extreme heat (30+ degrees Celsius days) shows a robust and large association with income loss (-$2.17M and -$2.10M per county). For insurance, the asymmetry reverses. Moderate to extreme drought is significantly associated with indemnity increases across all four insurance measures whereas temperature bins show only scattered and inconsistent significance for insurance outcomes, which is also consistent with the individual model results.

Chapter 6

A comparison between the Palmer Z-index and the Temperature-precipitation Specification

A difficulty persists in choosing how to quantify and assess hydrometeorological hazards. Droughts are complex phenomena that can be approached from multiple directions. Monthly temperature and precipitation are two key components that are used in conjunction with other variables to construct the Palmer Z-index. Hence, a direct comparison of the results from the Palmer Z-index model and the direct temperature and precipitation model provides a contrast between a composite drought index and direct weather variables with much shorter reporting intervals.

The Palmer Z-index is designed to quantify monthly moisture anomalies relative to historically normal conditions whereas the temperature bin model exploits the daily thermal exposure of crops to identify nonlinear effects. The Z-index captures a mixture of the two distinct mechanisms of temperature and precipitation. Therefore, a comparison with the temperature-precipitation model estimates can provide some insight into how the Z-index estimates compare with direct temperature and precipitation effects.

Figure 6.1 shows mean growing season days per county over the 2002 to 2023 period for all Palmer Z-index categories and all temperature bins. Moderate to extreme and mild drought categories from the Palmer Z-index show that droughts are highly episodic - both remain close to zero with occasional spikes. The only exception was 2012 which represents a massive drought inflicted year. The mild drought categories are consistently more frequent than the moderate to extreme drought categories as expected. The wet condition categories (mild wet and moderate to extreme wet) show less pronounced spikes and greater year-to-year variability, with no single dominating event. For the temperature bins, the cool to moderately warm bins show no significant trend which is expected for the study region during the growing season. The 25-30 degrees Celsius bin shows moderate year-to-year variation and the 30+ degrees bin shows some upward spikes in the more recent years. This is consistent with the broader warming trend documented in the climate literature.

Figure 6.2 shows Pearson's r correlation between each of the four Palmer Z-index categories and each of the six temperature bins. Here, the 15-20 degrees reference bin shows almost zero correlations with all the Palmer Z-index categories never even reaching 0.1, confirming that it represents a neutral baseline condition with respect to both drought and excess moisture. The warmer bins between 20 and 30 degrees Celsius show moderate correlation whereas the 30+ degrees bin shows very high correlation with drought categories. The moderate to extreme drought category and the 30+ degrees Celsius bin tend to move together but still have some independent variation.

Figure 6.3 exhibits a standardized comparison between the coefficients of the moderate to extreme drought category and the 30+ degrees bin. This is an effect size comparison between the two specifications for all eight agricultural outcomes. In order to standardize, each coefficient is multiplied by the standard deviation of its variable - 3.852 pentads for the moderate to extreme drought Z-Index and 3.736 days for the 30+ degrees temperature bin - so both estimates reflect the predicted response to a one standard deviation increase in weather stress or hazard shock expressed in comparable units. It is a comparison between the most extreme categories in each specification.

The filled circles indicate significance at the 5 percent level under the Conley spatial HAC standard errors at 425 km cutoff. The hollow circles indicate insignificance at the 5 percent level. The three panels show where these two categories/bins converge and where they diverge. The first panel for yields shows that both specifications identify statistically significant yield reductions per one standard deviation shock. It shows that one standard deviation shock is associated with a reduction of corn yields by approximately 8.7 percent under the Z-index and 11.7 percent under the temperature bin specification. The two specifications agree in direction and both survive spatial correction. This provides evidence on the yield damage channel being convergent for these two categories.

The income panel shows something very different. The temperature bin specification identifies large and significant income losses of approximately $7.7 million per county per standard deviation shock for both operations and producers income whereas the Z-index does not. The Z-index estimates are small, centered near zero and statistically indistinguishable from zero under the Conley spatial HAC standard error correction. This divergence reflects that extreme heat above 30 degrees leads to acute reduction in production. That reduction feeds directly through to income while the composite drought or moisture anomaly index is more diffuse and less precise for income regressions.

The insurance panel shows the opposite pattern. The moderate to extreme drought Z-index estimates for total RMA indemnities, RMA corn indemnities and RMA soy indemnities are positive, large in magnitude and statistically significant. The 30+ degrees temperature bin however, shows mostly insignificant associations except for the RMA soy indemnities. This asymmetric result reflects that the federal crop insurance system is more aligned with the Palmer Z-index and the Palmer Z-index moderate to extreme drought category captures these insurance payouts more directly.

These three figures together show that the Palmer Z-index and the temperature bin specifications are capturing complementary dimensions of hydrometeorological shocks. Each specification has a comparative advantage in identifying particular channels of economic and biophysical impacts. The Z-index specification responds more to the insurance channel and temperature bin specification responds more to the income channel. Both specifications respond well to the yield channel.

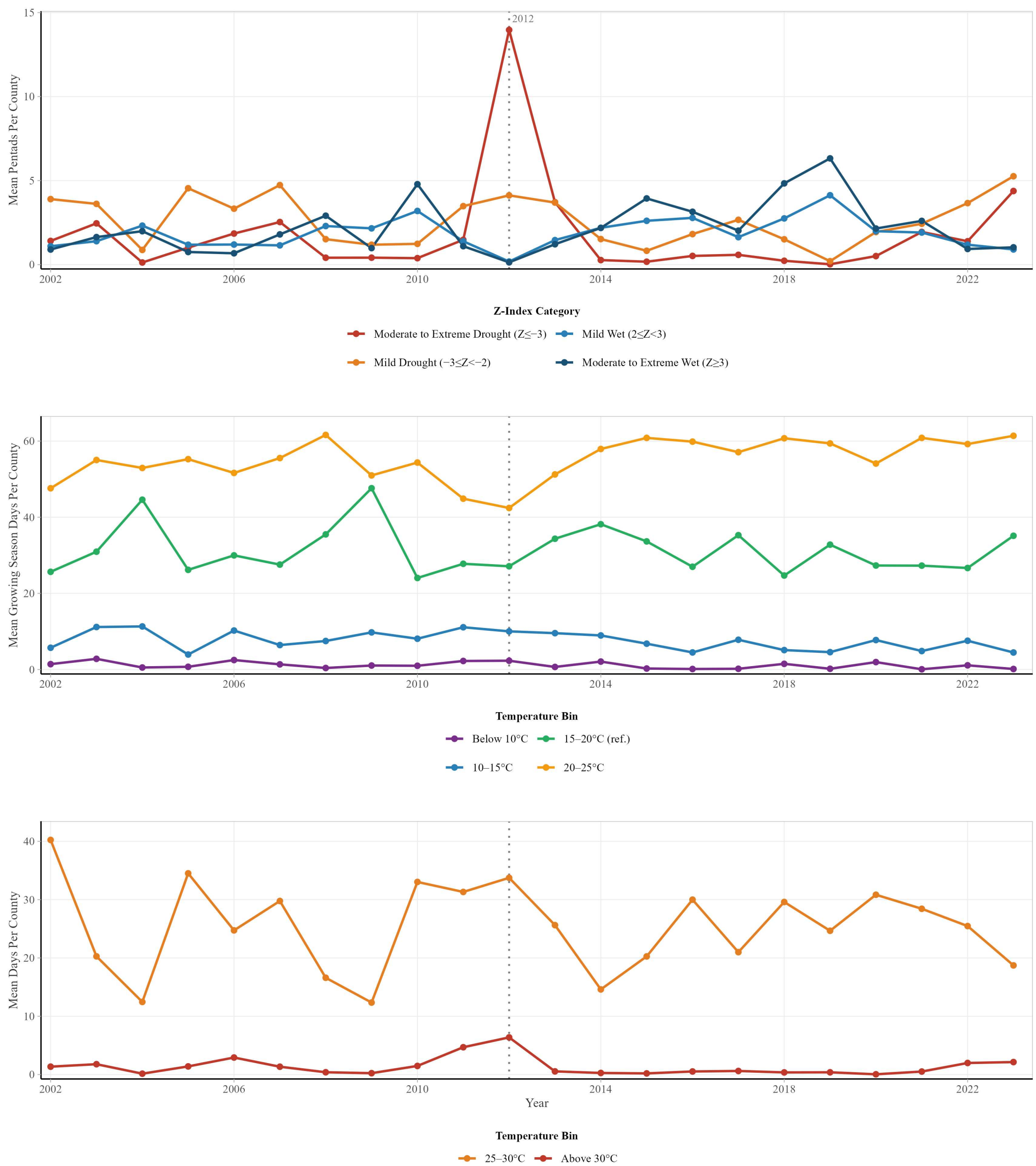

Figure 6.1: Mean Days Per County: Palmer Z-index Bins vs Temperature Bins

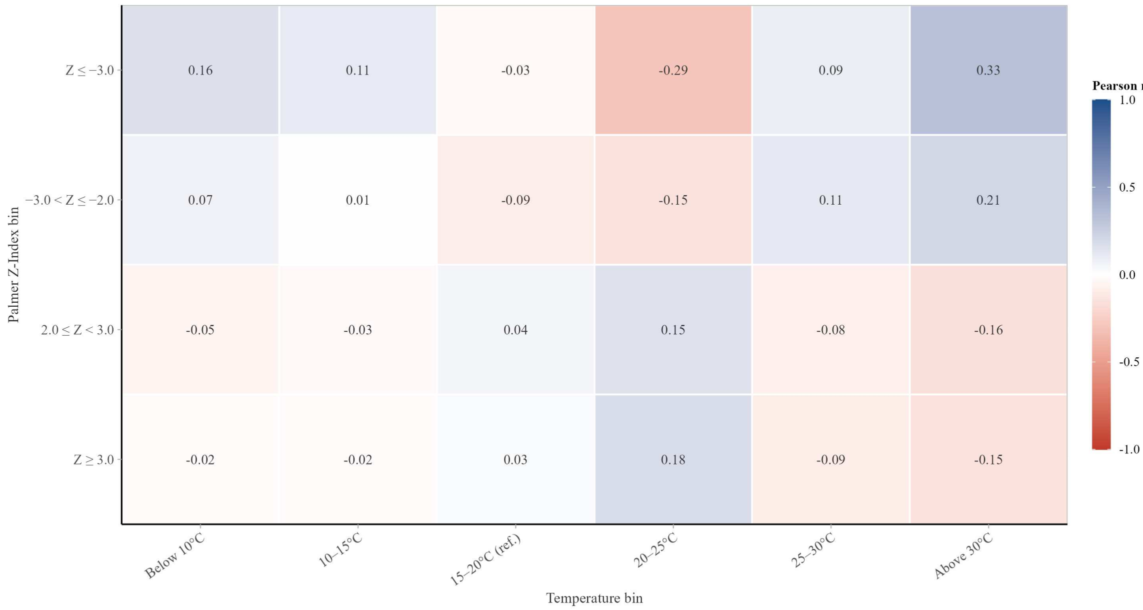

Figure 6.2: Pearson Correlation between Z-Index Bins and Temperature Bins

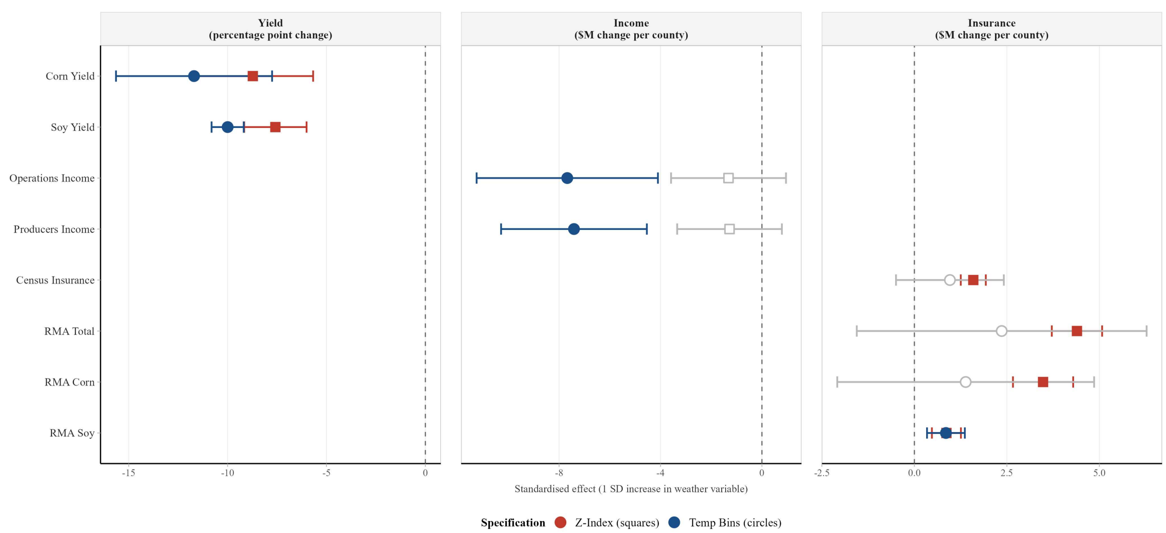

Figure 6.3: Comparison of the Moderate to Extreme Drought Category (Palmer Z-index) and Severe Heat (30+ Degrees Celsius) Coefficients

6.1 Corn and Soybean Market Prices

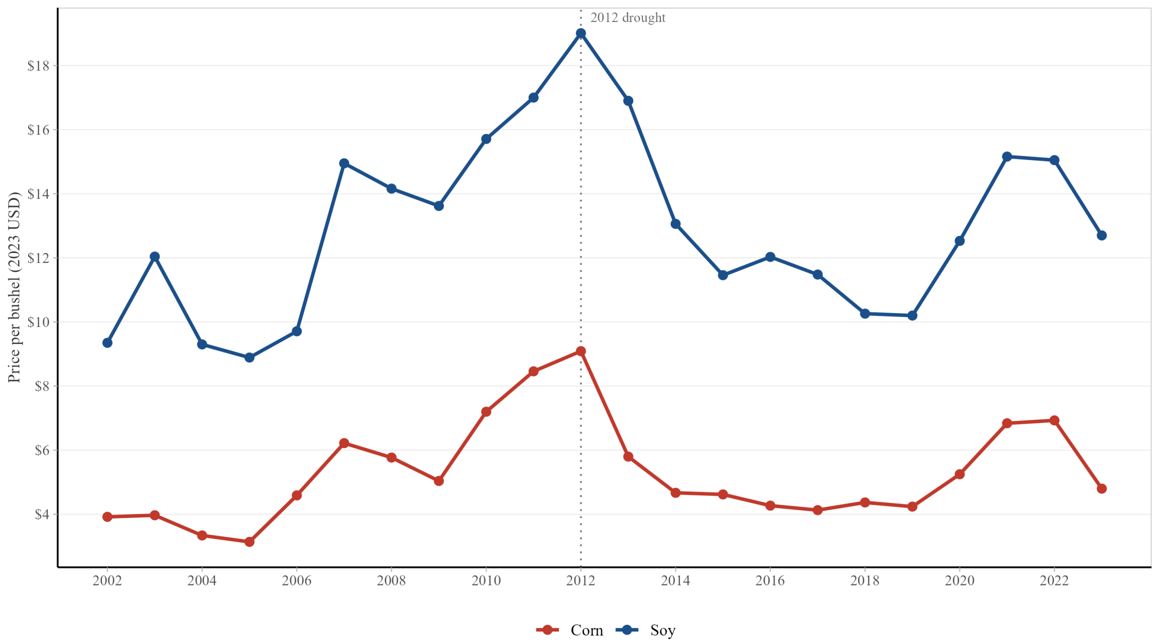

Figure 6.4: Real Corn and Soybean Prices

(National Agricultural Statistics Service, USDA, 2023)

Figure 6.4 shows the corn and soybean prices adjusted for inflation in 2023 U.S. dollars spanning from 2002 to 2023. Both crop prices rise sharply in 2012 which is supportive evidence of a market response of prices to the massive 2012 drought. Corn hit approximately $9 dollars per bushel and soybean hit approximately $19 dollars per bushel.

However, it should be interpreted with caution as descriptive rather than causal evidence. Prices can trend upward for reasons unrelated to drought such as input costs, biofuel demand and global market conditions.

The econometric specifications used in this paper are suited to identifying the effect of hydrometeorological shocks on yields, income, and insurance transfers but they are not designed to identify price effects. This is because corn and soybean prices are not set at the county level. They are mostly set by global supply and demand. A specification with county and year fixed effects identifies coefficients from the within-county and within-year deviation in the outcome variable, conditional on the regressors. Had prices been measured at the county level, it would be near-identical across counties within a state in the same year and would therefore be absorbed almost entirely by the year fixed effects leaving little to no residual variation for the weather variables to explain. Therefore, including price as an outcome in a county-level specification would not be appropriate as it would not be able to isolate a meaningful price response to local hydrometeorological shocks.

Chapter 7

Summary of Findings

This paper provides new county level evidence on how growing season droughts, floods and temperature are associated with agricultural yields, farm income and insurance payments in the U.S. Midwest. The study provides the following principal findings:

Moderate to extreme growing season droughts are strongly associated with crop yields negatively. Each additional pentad of moderate to extreme drought is associated with a 2.27 percent reduction in corn yields and a 1.97 percent reduction in soybean yields. These results are based on two-way fixed effects models using county and year fixed effects, ruling out confounding from time-invariant county characteristics and aggregate national shocks. Mild droughts also have negative yield associations, showing reductions of 1.04 percent for corn and 1.14 percent for soybeans per pentad. Mild wet conditions do not have robust and statistically significant associations with either yield variable but moderate to extreme wet conditions have robust and significant negative associations with both yield variables. The number of flood events in a county during the growing season has insignificant association with any of the yield outcomes. For the temperature bin models, the results show similar patterns. It can be seen that the 30+ and the 25-30 degrees bins both have negative associations with both yield variables, in comparison to the reference bin of 15-20 degrees Celsius. The 10-15 degrees bin also shows negative associations with both yield variables.

Moderate to extreme drought is not significantly associated with net farm income. One additional pentad of moderate to extreme drought shows reductions of approximately \$0.34 million for operations income and \$0.33 million for producers income but these results are not robust to spatial correlation. At the same time, each additional pentad of moderate to extreme drought is significantly associated with a \$0.41 million increase in insurance receipts as per the USDA census. The moderate to extreme wet category of the Palmer Z-index is the only category that shows significant associations - all negative - with the income variables using Conley standard errors. The temperature bin model shows positive robust associations between the 25-30 degrees category and all the insurance variables indicating higher need for insurance claims for that temperature window. The 20-25 degrees bin shows negative associations with the census insurance variable, the total crop indemnity payments by RMA and corn specific indemnity payments. The 30+ bin has a robust positive association with only the indemnity payments for soy. The precipitation and its squared term are robust for only the Soy payments.

An additional set of results pertaining to the acreage responses from hydrometeorological hazards and weather shocks are provided in Appendix A.6 table A.19 and table A.20. The results show that acreage response is associated with these hazards during different planting windows. This provides evidence for the extensive margin of the biophysical pathway of the conceptual model - beyond the effect of hazards on yields, farmers also adjust how much of each crop they plant in response to these hazards and weather conditions. The 30+ bin during the planting season (April-May) is associated with an increase in soybean planted acres by 11.7%. This suggests a shift towards soybean planting when Springs are exceptionally warm. Growing season temperature extremes don't show any statistically significant effect on either crop's planted acreage. However, the Palmer Z-index drought categories do show associations with corn and soybean planted acreage. Moderate to extreme drought during the growing season reduces soybean planted and harvested acres by 0.31% and 0.51% respectively. Appendix A.4 tables A.13 and A.14 provide income per acre regression results which show that that the drought index and the temperature-precipitation specifications explain very little of the within-county variation of per acre income. The only effects that survive are the negative associations of moderate to extreme drought and severe heat (30+ degrees Celsius) on producers income per acre.

It is safe to say that the impacts of hydrometeorological hazards are strong and robust for yields. The income effects on the other hand, are more imprecise. Droughts categorized by the Palmer Z-index have weak and imprecise associations with farm income but temperature shocks have large and statistically significant associations with income. Insurance responds robustly to drought with large increases in indemnity payments but responses to temperature shocks are weaker and less consistent. This suggests potential gaps in coverage for heat related risks.

Chapter 8

Conclusion

The results of this study clearly show that growing season hydrometeorological hazards and weather shocks are significantly associated with agricultural outcomes in the U.S. Midwest. The effects of extreme heat are large in particular and are already being realized. It is important to draw out the implications of these findings for policy and practice while acknowledging limitations and identifying most productive directions for future research.

The most immediate policy relevant finding is how crop insurance responds differently to different hydrometeorological hazards. The other important result is the magnitude and robustness of the association of severe heat - days above 30 degrees Celsius - on the two major crops in the U.S. Midwest. The fact that the results survive spatial correction and hold across a 22 year panel of 889 counties says that these are realized losses that farmers have already experienced. The estimates for the moderate to extreme drought category specified here from the Palmer Z-index provides a similar message. Under global warming scenarios, these extreme heat days would be expected to increase and thus it provides a warning message to the agricultural economy of the U.S. Midwest.

The federal crop insurance programs are partially absorbing the financial damages. The results suggest that indemnity payments are partially compensating for the losses. Policymakers should pay attention to decreasing the gap between insured and realized losses by evaluating the adequacy of current coverage structures focusing on both drought and extreme heat events.

The precipitation findings carry some important insights. Corn and soy both show inverted-U relationships with growing season average daily precipitation. It can be seen that roughly 60% of the county-years fall below the daily optimum precipitation threshold for corn. This implies that a moderate increase in growing season precipitation would be enhancing for corn yield across most of the region under current conditions - therefore, counties in the left arm of the precipitation curve face a fundamentally different risk profile than those receiving excess moisture. This finding could be helpful for policymakers working with irrigation and water resource allocation.

Now, to address limitations of this study, some issues must be discussed. Firstly, farm income and insurance data are only available for census years. Therefore, there are limitations in the income and insurance regressions. Secondly, the study focuses on the U.S. Midwest which is appropriate, given that the two primary crops studied are corn and soybean. This however, implies that the results could vary with other crop type and also vary for other geographic areas. Thirdly, droughts, floods and extreme temperature episodes are key hydrometeorological hazards but are a subset of a much larger group of hazards. The estimates found in this study might not highly correlate with other forms of hydrometeorological hazards.

A good line of extension for this work would be the incorporation of within-season weather timing. Crop sensitivity is non-uniform to heat and hazards across the growing season. Different stages of crop growth interact differently with these shocks. If daily weather records can be linked to crop growth phases or phenological calendars, that would allow for stage-specific damage functions and most probably reveal much larger associations. The second important extension would be to incorporate the adaptation margin more broadly. Adaptation spans a broad range of decisions that cannot be revealed by county-level aggregate data and requires data at a more micro level. Administrative microdata could help link farm decisions to weather realizations. This would reveal a wide array of heterogeneous impacts. Future research could also investigate how insurance participation rates, coverage and premiums respond to local climate conditions over time. This would require finer insurance data. The third important extension would be to explore the effects of these hazards on disaster/relief payments in a parallel analysis. It would help us understand the extent to which these payments are impacted by drought and heat occurrences.

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Appendix A

Additional Tables

A.1 Variable Descriptions

Table A.1: Variable Definitions: Outcome Variables

Variable	Units	Description
Outcome Variables		
Log Corn Yield	Log(bu/acre)	Natural log of corn yield per harvested acre
Log Soy Yield	Log(bu/acre)	Natural log of soybean yield per harvested acre
Operations Income ($M)	Millions USD	Total farm operations income
Producers Income ($M)	Millions USD	Total farm producer income
Operations Income/Acre ($/acre)	USD/acre	Farm operations income per planted acre
Producers Income/Acre ($/acre)	USD/acre	Farm producer income per planted acre
Census Insurance ($M)	Millions USD	Crop and livestock insurance receipts (USDA Census)
RMA Total Indemnity ($M)	Millions USD	Total RMA indemnity payments (all crops)
RMA Corn Indemnity ($M)	Millions USD	RMA indemnity payments for corn
RMA Soy Indemnity ($M)	Millions USD	RMA indemnity payments for soybeans

Notes: Census years: 2002, 2007, 2012, 2017, 2022. RMA years: 2007, 2012, 2017, 2022.

Table A.2: Variable Definitions: Palmer Z-Index (Moisture Anomalies)

Variable	Units	Description
Palmer Z-Index (April-May, June-September, January-September)		
Moderate to Extreme Drought	Pentad count	Pentads with Palmer Z-index $Z < -3.0$
Mild Drought	Pentad count	Pentads with $-3.0 \leq Z < -2.0$
Mild Wet	Pentad count	Pentads with $2.0 \leq Z < 3.0$
Moderate to Extreme Wet	Pentad count	Pentads with $Z \geq 3.0$
Total Floods (Jun-Sep only)	Count	Flood events during June-September (NOAA)

Notes: Pentad = 5-day period (2002-2023).

Growing season models include flood control. The categories are consistent with Gridmet classifications.

Table A.3: Variable Definitions: Temperature and Precipitation

Variable	Units	Description
Temperature Bins (5°C Intervals)		
Below 10°C	Days	Days with mean temperature < 10°C
10-15°C	Days	Days with mean temperature $10 - 15$°C
15-20°C (Reference)	Days	Days with mean temperature $15 - 20$°C (omitted)
20-25°C	Days	Days with mean temperature $20 - 25$°C
25-30°C	Days	Days with mean temperature $25 - 30$°C
30°C+	Days	Days with mean temperature > 30°C
Precipitation		
Mean Precipitation	mm/day	Average daily precipitation
Mean Precipitation Squared	$(\text{mm/day})^2$	Square of average daily precipitation

Notes: Coverage: 2002-2023. Temperature reference category: 15-20°C (omitted from regressions).

A.1.1 Moran's I Spatial Autocorrelation Diagnostics

Table A.4: Moran's I Test Results for Model Residuals (k=8 Nearest Neighbors)

Model	Moran's I	p-value	Significant	Interpretation
Palmer Z-Index Models				
Corn Yield	0.1627	0.0000	***	Moderate
Soy Yield	0.1935	0.0000	***	Moderate
Operations Income ($M)	0.0738	0.0000	***	Mild
Producers Income ($M)	0.0936	0.0000	***	Mild
Operations Income/Acre	0.0254	0.0805		None
Producers Income/Acre	-0.0017	0.9702		None
Census Insurance ($M)	0.0486	0.0020	**	Mild
RMA Total Indemnity ($M)	0.0305	0.0472	*	Mild
RMA Corn Indemnity ($M)	0.1011	0.0000	***	Moderate
RMA Soy Indemnity ($M)	0.0345	0.0273	*	Mild
Temperature Bin Models				
Corn Yield	0.1202	0.0000	***	Moderate
Soy Yield	0.0689	0.0000	***	Mild
Operations Income ($M)	-0.0117	0.5113		None
Producers Income ($M)	0.0046	0.7215		None
Operations Income/Acre	-0.0025	0.9256		None
Producers Income/Acre	0.0110	0.4057		None
Census Insurance ($M)	0.0546	0.0006	***	Mild
RMA Total Indemnity ($M)	0.0277	0.0734		None
RMA Corn Indemnity ($M)	0.0247	0.1099		None
RMA Soy Indemnity ($M)	0.0353	0.0242	*	Mild
Summary Statistics				
Total models tested	20			
Significant ($p < 0.05$)	12			
Mean Moran's I	0.0547			
Max Moran's I	0.1935			

Notes: Moran's I using k=8 nearest-neighbor weights. Significance: *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.
I thresholds: < 0.05 negligible, $0.05 - 0.10$ mild, $0.10 - 0.20$ moderate, ≥ 0.20 substantial.
All models include county and year FE.

A.1.2 Spatial Correlation Plot

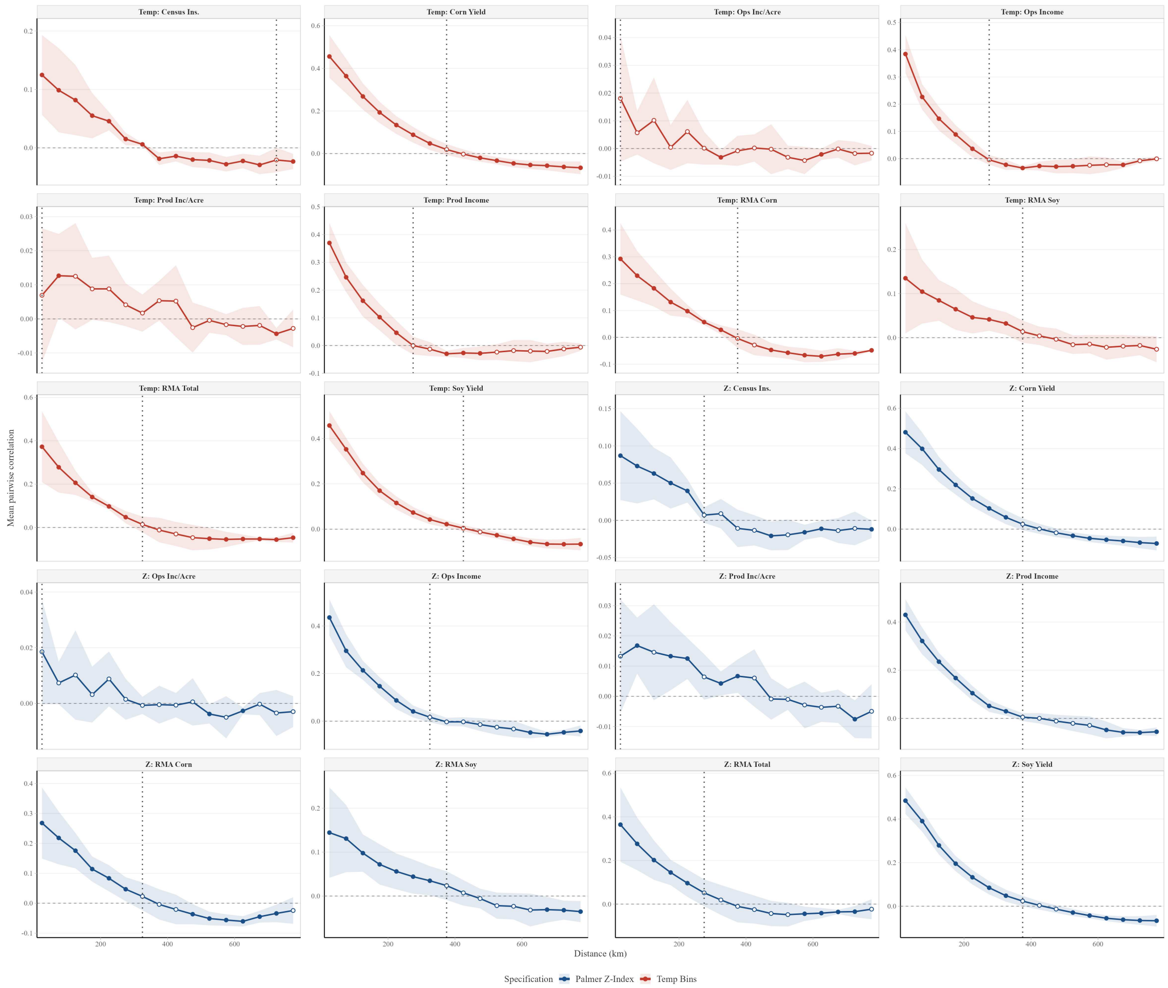

Figure A.1: Residual Correlogram

Notes: Pairwise residual correlations computed within each year then averaged across years. The gray dotted vertical line in each panel marks the natural Conley bandwidth — the midpoint of the first 50 km band whose 95% confidence interval includes zero. Transparent points show statistical insignificance.

A.2 Planting Season/Extended Regression Results

This appendix presents the complete baseline regression results for two more seasons along with the growing season specification: planting season (April to May) and extended season (January to September). The flood count variable was omitted from the planting season and extended season specifications. All models include county and year fixed effects, with standard errors clustered at the county level.

Table A.5: Planting Season Regressions (April–May) — Conley SE (425 km)

	Yield		Income ($M)		Insurance ($M)	
	Corn	Soy	Operations	Producers	Census	RMA Total
Palmer Z-Index						
Moderate to Extreme Drought	0.00040	-0.01009	0.70718	0.50562	0.60269^{**}	1.68657^{***}
	$[0.00424]$	$[0.00609]$	$[0.57019]$	$[0.60850]$	$[0.22001]$	$[0.46403]$
Mild Drought	-0.00530	-0.00989^{**}	-1.47103^{***}	-1.05860^{***}	0.38762^{*}	1.44659^{***}
	$[0.00349]$	$[0.00363]$	$[0.42756]$	$[0.31078]$	$[0.17240]$	$[0.40870]$
Mild Wet	-0.00519^{*}	-0.00463^{*}	-0.09011	0.16758	-0.13886	-0.31091
	$[0.00258]$	$[0.00232]$	$[0.35549]$	$[0.33486]$	$[0.09248]$	$[0.22761]$
Moderate to Extreme Wet	-0.00505	-0.00254	0.26632	0.48844	0.21423^{*}	0.58447^{*}
	$[0.00298]$	$[0.00330]$	$[0.43802]$	$[0.32896]$	$[0.10364]$	$[0.23006]$
Temperature Bins (ref: 15-20°C)						
Below 10°C	0.00370	0.00164	0.314	0.142	-0.196	-0.447
	$[0.00216]$	$[0.00331]$	$[0.570]$	$[0.469]$	$[0.106]$	$[0.286]$
10-15°C	0.00103	-0.00166	0.099	-0.032	-0.136	-0.382
	$[0.00209]$	$[0.00238]$	$[0.274]$	$[0.213]$	$[0.098]$	$[0.308]$
20-25°C	0.00154	0.00189	-0.086	-0.282	-0.111	-0.423^{*}
	$[0.00183]$	$[0.00243]$	$[0.358]$	$[0.308]$	$[0.065]$	$[0.189]$
25-30°C	-0.02365^{***}	-0.01108	-2.058	-1.920	-0.017	0.273
	$[0.00121]$	$[0.00694]$	$[1.742]$	$[1.553]$	$[0.265]$	$[0.760]$
30°C+	0.00261	-0.00099	–	–	–	–
	$[0.03925]$	$[0.02127]$				
Precip (mm)	0.01687	0.01679	-2.831	-2.505	-0.706	-2.502
	$[0.01221]$	$[0.01173]$	$[2.146]$	$[1.728]$	$[0.555]$	$[1.645]$
Precip Sq	-0.00251	-0.00187	0.528	0.485^{*}	0.064	0.236
	$[0.00167]$	$[0.00182]$	$[0.284]$	$[0.246]$	$[0.055]$	$[0.158]$
Obs	16,720	16,560	4,070	4,069	3,047	3,189
Counties (Z/Temp)	878/887	874/883	880/889	880/889	854/863	879/888
Years	22	22	5	5	4	4
Adj. R^2 (Z/Temp)	0.667/0.673	0.691/0.689	0.749/0.753	0.763/0.768	0.385/0.351	0.359/0.313
Within R^2 (Z/Temp)	0.006/0.027	0.016/0.012	0.008/0.025	0.010/0.032	0.066/0.018	0.091/0.029
RMSE (Z/Temp)	0.164/0.163	0.150/0.151	22.0/21.8	18.0/17.8	3.140/3.210	8.264/8.526

Notes: Conley SEs in brackets [].

Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Reference category: 15-20°C. ($-$) not estimated.

Table A.6: Extended Season Regressions (January–September) — Conley SE (425 km)

	Yield		Income ($M)		Insurance ($M)	
	Corn	Soy	Operations	Producers	Census	RMA Total
Palmer Z-Index						
Moderate to Extreme Drought	-0.01593^{***}	-0.01488^{***}	-0.27565	-0.26077	0.36090^{***}	1.01359^{***}
	[0.00289]	[0.00150]	[0.19202]	[0.16030]	[0.04769]	[0.09009]
Mild Drought	-0.00287	-0.00624^{***}	0.34889	0.39842^{**}	-0.04422	-0.08313
	[0.00165]	[0.00153]	[0.18617]	[0.14418]	[0.03204]	[0.12352]
Mild Wet	-0.00116	-0.00057	-0.26259	-0.14596	-0.04920	-0.04199
	[0.00130]	[0.00098]	[0.22953]	[0.17221]	[0.05632]	[0.11228]
Moderate to Extreme Wet	-0.00430^{**}	-0.00255^{*}	0.04086	0.17455	0.07393	0.17346
	[0.00143]	[0.00111]	[0.21366]	[0.21163]	[0.05401]	[0.11601]
Temperature Bins (ref: 15-20°C)						
Below 10°C	-0.00073	-0.00297^{*}	-0.324^{*}	-0.346^{**}	-0.127^{**}	-0.277^{*}
	[0.00153]	[0.00119]	[0.160]	[0.130]	[0.041]	[0.112]
10-15°C	-0.00070	-0.00330^{**}	-0.106	-0.120	-0.026	-0.108
	[0.00105]	[0.00127]	[0.198]	[0.169]	[0.056]	[0.124]
20-25°C	0.00019	-0.00018	0.214	0.152	-0.084^{**}	-0.328^{***}
	[0.00085]	[0.00078]	[0.166]	[0.118]	[0.027]	[0.075]
25-30°C	-0.00635^{***}	-0.00563^{***}	-0.419	-0.435	0.134^{*}	0.333^{**}
	[0.00154]	[0.00087]	[0.273]	[0.262]	[0.064]	[0.113]
30°C+	-0.03195^{***}	-0.02736^{***}	-1.865^{**}	-1.825^{***}	0.205	0.485
	[0.00547]	[0.00164]	[0.567]	[0.465]	[0.171]	[0.477]
Precip (mm)	0.07586	0.13545^{***}	-18.438^{**}	-14.153^{**}	-6.487^{***}	-18.765^{***}
	[0.07645]	[0.02475]	[7.026]	[5.442]	[1.935]	[4.932]
Precip Sq	-0.01304	-0.01776^{**}	2.469	1.820	1.043^{***}	2.979^{***}
	[0.01332]	[0.00593]	[1.276]	[1.025]	[0.262]	[0.710]
Obs (Z/Temp)	16,720/16,896	16,560/16,740	4,070/4,113	4,069/4,112	3,047/3,077	3,189/3,222
Counties (Z/Temp)	878/887	874/883	880/889	880/889	854/863	879/888
Years	22	22	5	5	4	4
Adj. R^2 (Z/Temp)	0.692/0.742	0.722/0.761	0.748/0.761	0.762/0.778	0.432/0.452	0.402/0.441
Within R^2 (Z/Temp)	0.081/0.231	0.116/0.242	0.006/0.058	0.009/0.075	0.137/0.170	0.153/0.210
RMSE (Z/Temp)	0.158/0.144	0.143/0.132	22.1/21.4	18.0/17.3	3.018/2.951	7.978/7.690

Notes: Conley SEs in brackets []. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Reference category: 15-20°C.

A.3 Seasonal Comparison Tables

Table A.7: Seasonal Comparison: Palmer Z-Index — Yield

Outcome	Variable	Planting (Apr–May)	Growing (Jun–Sep)	Extended (Jan–Sep)
Log Corn Yield				
	Moderate to Extreme Drought	0.0004	−0.0226***	−0.0159***
		[0.0042]	[0.0040]	[0.0029]
	Mild Drought	−0.0053	−0.0104***	−0.0029
		[0.0035]	[0.0020]	[0.0016]
	Mild Wet	−0.0052*	−0.0009	−0.0012
		[0.0026]	[0.0014]	[0.0013]
	Moderate to Extreme Wet	−0.0050	−0.0075***	−0.0043**
		[0.0030]	[0.0014]	[0.0014]
Log Soy Yield				
	Moderate to Extreme Drought	−0.0101	−0.0197***	−0.0149***
		[0.0061]	[0.0021]	[0.0015]
	Mild Drought	−0.0099**	−0.0114***	−0.0062***
		[0.0036]	[0.0022]	[0.0015]
	Mild Wet	−0.0046*	0.0015	−0.0006
		[0.0023]	[0.0015]	[0.0010]
	Moderate to Extreme Wet	−0.0025	−0.0036***	−0.0026*
		[0.0033]	[0.0010]	[0.0011]

Notes: Conley SEs (425 km) in brackets []. Significance stars: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.
County and year fixed effects in all models. Growing season includes flood count control.

Table A.8: Seasonal Comparison: Palmer Z-Index — Income

Outcome	Variable	Planting (Apr–May)	Growing (Jun–Sep)	Extended (Jan–Sep)
Operations Income ($M)				
	Moderate to Extreme Drought	0.707	−0.342	−0.276
		[0.570]	[0.300]	[0.192]
	Mild Drought	-1.471^{***}	0.407	0.349
		[0.428]	[0.402]	[0.186]
	Mild Wet	−0.090	−0.721	−0.263
		[0.355]	[0.709]	[0.230]
	Moderate to Extreme Wet	0.266	-0.402^{*}	0.041
		[0.438]	[0.157]	[0.214]
Producers Income ($M)				
	Moderate to Extreme Drought	0.506	−0.332	−0.261
		[0.609]	[0.274]	[0.160]
	Mild Drought	-1.059^{***}	0.403	0.398^{**}
		[0.311]	[0.382]	[0.144]
	Mild Wet	0.168	−0.619	−0.146
		[0.335]	[0.616]	[0.172]
	Moderate to Extreme Wet	0.488	-0.239^{**}	0.175
		[0.329]	[0.082]	[0.212]

Notes: Conley SEs (425 km) in brackets []. Significance stars: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. County and year fixed effects in all models. Growing season includes flood count control.

Table A.9: Seasonal Comparison: Palmer Z-Index — Insurance

Outcome	Variable	Planting (Apr–May)	Growing (Jun–Sep)	Extended (Jan–Sep)
Census Insurance ($M)				
	Moderate to Extreme Drought	0.603^{**}	0.413^{***}	0.361^{***}
		[0.220]	[0.045]	[0.048]
	Mild Drought	0.388^{*}	-0.062	-0.044
		[0.172]	[0.045]	[0.032]
	Mild Wet	-0.139	0.067	-0.049
		[0.092]	[0.146]	[0.056]
	Moderate to Extreme Wet	0.214^{*}	0.111	0.074
		[0.104]	[0.068]	[0.054]
RMA Total Indemnity ($M)				
	Moderate to Extreme Drought	1.687^{***}	1.141^{***}	1.014^{***}
		[0.464]	[0.090]	[0.090]
	Mild Drought	1.447^{***}	-0.162	-0.083
		[0.409]	[0.159]	[0.124]
	Mild Wet	-0.311	0.347	-0.042
		[0.228]	[0.431]	[0.112]
	Moderate to Extreme Wet	0.584^{*}	0.268	0.173
		[0.230]	[0.176]	[0.116]

Notes: Conley SEs (425 km) in brackets []. Significance stars: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. County and year fixed effects in all models. Growing season includes flood count control.

Table A.10: Seasonal Comparison: Temperature Bins — Yield

Outcome	Variable	Planting (Apr–May)	Growing (Jun–Sep)	Extended (Jan–Sep)
Log Corn Yield				
	Below 10°C	0.00370	−0.00079	−0.00073
		[0.00216]	[0.00541]	[0.00153]
	10–15°C	0.00103	−0.00205*	−0.00070
		[0.00209]	[0.00086]	[0.00105]
	20–25°C	0.00154	0.00016	0.00019
		[0.00183]	[0.00072]	[0.00085]
	25–30°C	−0.02365***	−0.00589***	−0.00635***
		[0.00121]	[0.00143]	[0.00154]
	30+°C	0.00261	−0.03131***	−0.03195***
		[0.03925]	[0.00539]	[0.00547]
Log Soy Yield				
	Below 10°C	0.00164	0.00169	−0.00297*
		[0.00331]	[0.00436]	[0.00119]
	10–15°C	−0.00166	−0.00411*	−0.00330**
		[0.00238]	[0.00175]	[0.00127]
	20–25°C	0.00189	−0.00079	−0.00018
		[0.00243]	[0.00075]	[0.00078]
	25–30°C	−0.01108	−0.00577***	−0.00563***
		[0.00694]	[0.00090]	[0.00087]
	30+°C	−0.00099	−0.02676***	−0.02736***
		[0.02127]	[0.00111]	[0.00164]

Notes: Conley SEs (425 km) in brackets []. Significance stars: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Reference category: 15–20°C.

Table A.11: Seasonal Comparison: Temperature Bins — Income

Outcome	Variable	Planting (Apr–May)	Growing (Jun–Sep)	Extended (Jan–Sep)
Operations Income ($M)				
	Below 10°C	0.314	-1.907^{**}	-0.324^{*}
		[0.570]	[0.647]	[0.160]
	10–15°C	-0.215	1.222^{*}	0.218
		[0.313]	[0.610]	[0.213]
	20–25°C	-0.401	2.040^{***}	0.537^{**}
		[0.715]	[0.556]	[0.173]
	25–30°C	-2.373	1.330^{***}	-0.096
		[1.782]	[0.403]	[0.196]
	30+°C	–	-0.148	-1.865^{**}
			[0.417]	[0.567]
Producers Income ($M)				
	Below 10°C	0.142	-1.712^{**}	-0.346^{**}
		[0.469]	[0.595]	[0.130]
	10–15°C	-0.174	1.119^{*}	0.227
		[0.273]	[0.566]	[0.206]
	20–25°C	-0.424	1.819^{**}	0.498^{***}
		[0.596]	[0.609]	[0.136]
	25–30°C	-2.062	1.146^{*}	-0.088
		[1.530]	[0.510]	[0.213]
	30+°C	–	-0.272	-1.825^{***}
			[0.556]	[0.465]

Notes: Conley SEs (425 km) in brackets []. Significance stars: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Reference category: 15–20°C. (–) indicates not estimated due to data limitations.

Table A.12: Seasonal Comparison: Temperature Bins — Insurance

Outcome	Variable	Planting (Apr–May)	Growing (Jun–Sep)	Extended (Jan–Sep)
Census Insurance ($M)				
	Below 10°C	-0.196	0.029	-0.127^{**}
		[0.106]	[0.085]	[0.041]
	10–15°C	0.060	0.097	0.101
		[0.094]	[0.058]	[0.062]
	20–25°C	0.085	-0.082^{**}	-0.084^{**}
		[0.104]	[0.029]	[0.027]
	25–30°C	0.179	0.129^{*}	0.134^{*}
		[0.306]	[0.065]	[0.064]
	30+°C	–	0.257	0.205
			[0.199]	[0.171]
RMA Total Indemnity ($M)				
	Below 10°C	-0.447	0.108	-0.277^{*}
		[0.286]	[0.211]	[0.112]
	10–15°C	0.065	0.226	-0.108
		[0.237]	[0.127]	[0.124]
	20–25°C	-0.423^{*}	-0.319^{***}	-0.328^{***}
		[0.189]	[0.093]	[0.075]
	25–30°C	0.720	0.326^{***}	0.333^{**}
		[0.856]	[0.092]	[0.113]
	30+°C	–	0.632	0.485
			[0.535]	[0.477]

Notes: Conley SEs (425 km) in brackets []. Significance stars: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Reference category: 15–20°C. ($-$) indicates not estimated due to data limitations.

A.4 Income Per Acre Models

Table A.13: Palmer Z-Index: Income Per Acre Regressions

	Operations Income/Acre	Producers Income/Acre
Moderate to Extreme Drought	-6.6849	-7.0426^{*}
	(3.7627)	(3.5058)
	$[3.8468]$	$[3.8544]$
Mild Drought	1.5783	1.9256
	(2.1262)	(1.9179)
	$[2.1860]$	$[1.4629]$
Mild Wet	0.1720	-3.6134
	(4.7488)	(3.3992)
	$[6.5273]$	$[4.8851]$
Moderate to Extreme Wet	-8.4874	-6.3919
	(5.0893)	(3.8276)
	$[6.6664]$	$[4.7461]$
Floods	16.3603	9.9579
	(12.5701)	(7.3306)
	$[14.8891]$	$[8.5358]$
Observations	4,007	4,006
Counties	869	869
Years	5	5
Adj. R^2	0.239	0.183
Within R^2	0.003	0.004
RMSE	491.1	413.7

Notes: SE: () county, [] Conley (425 km).

Significance stars correspond to Conley SEs: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table A.14: Temperature Bin: Income Per Acre Regressions

	Operations Income/Acre	Producers Income/Acre
Below 10°C	6.9046	3.4431
	(5.8404)	(5.4754)
	$[8.5937]$	$[5.8419]$
10-15°C	-10.4707^{*}	-11.7142^{**}
	(4.5822)	(4.1497)
	$[5.9390]$	$[5.5627]$
20-25°C	4.3448^{*}	3.4808^{*}
	(1.8432)	(1.6081)
	$[3.1844]$	$[2.5936]$
25-30°C	6.9046	2.6396
	(3.7176)	(2.9643)
	$[5.8613]$	$[3.4617]$
30+°C	-1.5262	-7.0641^{*}
	(3.5232)	(2.9751)
	$[4.4186]$	$[3.5766]$
Precipitation (mm)	-6.2751	-29.0652
	(33.4248)	(30.0774)
	$[16.5769]$	$[25.8227]$
Precipitation Sq	3.1032	3.9757
	(5.2034)	(4.8682)
	$[3.1652]$	$[3.9707]$
Observations	4,074	4,073
Counties	883	883
Years	5	5
Adj. R^2	0.243	0.189
Within R^2	0.008	0.012
RMSE	486.4	409.1

Notes: Reference category: 15-20°C. SE: () county, [] Conley (425 km).

Significance stars correspond to Conley SEs: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

A.5 Robustness Check: Excluding 2012

Table A.15: Palmer Z-Index: Yield and Income Regressions (Excluding 2012)

	Yield		Income ($M)	
	Corn	Soy	Operations	Producers
Moderate to Extreme Drought	-0.0192^{***}	-0.0188^{***}	-0.4409	-0.4245
	(0.0011)	(0.0009)	(0.2065)	(0.1717)
	[0.0036]	[0.0013]	[0.3423]	[0.3059]
Mild Drought	-0.0127^{***}	-0.0122^{***}	0.4275	0.4377
	(0.0006)	(0.0006)	(0.2100)	(0.1637)
	[0.0023]	[0.0027]	[0.5176]	[0.4880]
Mild Wet	-0.0008	0.0013	-0.7569	-0.6456
	(0.0006)	(0.0006)	(0.3944)	(0.3246)
	[0.0015]	[0.0014]	[0.8005]	[0.6686]
Moderate to Extreme Wet	-0.0073^{***}	-0.0035^{**}	-0.2415	-0.0540
	(0.0004)	(0.0004)	(0.2248)	(0.1831)
	[0.0015]	[0.0013]	[0.3160]	[0.2155]
Floods	0.0002	-0.0004	0.1673	0.1820
	(0.0008)	(0.0006)	(0.3009)	(0.2737)
	[0.0015]	[0.0015]	[0.1516]	[0.0955]
Observations	15,813	15,653	3,170	3,169
Counties	873	867	874	874
Years	21	21	4	4
Adj. R^2	0.726	0.734	0.705	0.730
Within R^2	0.143	0.142	0.007	0.008
RMSE	0.136	0.136	23.2	18.4

Notes: SE: () county, [] Conley (425 km).

Significance stars correspond to Conley SEs: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table A.16: Temperature Bin: Yield and Income Regressions (Excluding 2012)

	Yield		Income ($M)	
	Corn	Soy	Operations	Producers
Below 10°C	-0.0021	-0.0002	-3.1727^{**}	-2.7127^{*}
	(0.0012)	(0.0013)	(0.6550)	(0.5411)
	[0.0038]	[0.0046]	[1.0878]	[1.2908]
10-15°C	-0.0023^{**}	-0.0042^{*}	-1.0549^{**}	-0.9197^{*}
	(0.0004)	(0.0006)	(0.2420)	(0.2111)
	[0.0009]	[0.0018]	[0.3428]	[0.3649]
20-25°C	-0.0014	-0.0012	0.0621	0.0349
	(0.0002)	(0.0002)	(0.1355)	(0.1034)
	[0.0008]	[0.0008]	[0.3081]	[0.2188]
25-30°C	-0.0071^{***}	-0.0063^{***}	-0.6721	-0.6284^{*}
	(0.0004)	(0.0004)	(0.1778)	(0.1258)
	[0.0012]	[0.0009]	[0.3507]	[0.2440]
30+°C	-0.0263^{***}	-0.0251^{***}	-2.2673^{***}	-2.2130^{***}
	(0.0014)	(0.0012)	(0.3205)	(0.2539)
	[0.0038]	[0.0013]	[0.6210]	[0.4418]
Precipitation (mm)	0.1297^{***}	0.1343^{***}	-13.2362^{*}	-12.0401^{**}
	(0.0074)	(0.0060)	(3.2239)	(2.5811)
	[0.0145]	[0.0135]	[6.1477]	[4.0825]
Precipitation Sq	-0.0158^{***}	-0.0149^{***}	1.6033^{*}	1.4578^{**}
	(0.0010)	(0.0007)	(0.4389)	(0.3541)
	[0.0019]	[0.0017]	[0.7394]	[0.5131]
Observations	16,075	15,919	3,223	3,222
Counties	887	881	888	888
Years	21	21	4	4
Adj. R^2	0.750	0.765	0.718	0.745
Within R^2	0.219	0.242	0.050	0.066
RMSE	0.130	0.128	22.6	17.9

Notes: Reference category: 15-20°C. SE: () county, [] Conley (425 km).

Significance stars correspond to Conley SEs: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table A.17: Palmer Z-Index: Insurance Regressions (Excluding 2012)

	Insurance Receipts ($M)			
	Census (All Crops)	RMA Total (All Crops)	RMA Corn	RMA Soy
Moderate to Extreme Drought	0.2175^{*}	0.6094^{**}	0.3712^{*}	0.2103^{***}
	(0.0319)	(0.0785)	(0.0564)	(0.0263)
	[0.0911]	[0.2279]	[0.1559]	[0.0526]
Mild Drought	0.0734^{*}	0.2426^{*}	0.1141^{*}	0.1195
	(0.0181)	(0.0450)	(0.0300)	(0.0186)
	[0.0358]	[0.1205]	[0.0523]	[0.0770]
Mild Wet	−0.0382	−0.0940	−0.1543	−0.0055
	(0.0331)	(0.0811)	(0.0567)	(0.0273)
	[0.0706]	[0.1885]	[0.1640]	[0.0336]
Moderate to Extreme Wet	0.0390	0.1254	0.0162	0.0276
	(0.0262)	(0.0541)	(0.0345)	(0.0190)
	[0.0759]	[0.1619]	[0.0914]	[0.0217]
Floods	0.1522	0.2889	0.2299	0.0757
	(0.0583)	(0.1193)	(0.0974)	(0.0407)
	[0.1127]	[0.3039]	[0.2454]	[0.0744]
Observations	2,119	2,223	2,178	2,174
Counties	776	801	783	781
Years	3	3	3	3
Adj. R^2	0.332	0.356	0.247	0.331
Within R^2	0.086	0.133	0.109	0.162
RMSE	1.838	4.219	2.944	1.461

Notes: SE: () county, [] Conley (425 km).

Significance stars correspond to Conley SEs: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table A.18: Temperature Bin: Insurance Regressions (Excluding 2012)

	Insurance Receipts ($M)			
	Census (All Crops)	RMA Total (All Crops)	RMA Corn	RMA Soy
Below 10°C	-0.1904	-0.8363^{*}	-0.5341^{*}	-0.2543^{**}
	(0.0814)	(0.2045)	(0.1703)	(0.0461)
	[0.1551]	[0.3856]	[0.2629]	[0.0909]
10-15°C	-0.0327	-0.1922	-0.1401	-0.0504
	(0.0220)	(0.0584)	(0.0467)	(0.0173)
	[0.0459]	[0.1356]	[0.0950]	[0.0455]
20-25°C	-0.0196	-0.0931	-0.0171	-0.0391
	(0.0130)	(0.0290)	(0.0185)	(0.0097)
	[0.0458]	[0.1282]	[0.0706]	[0.0414]
25-30°C	0.0274	-0.0055	0.0154	-0.0211
	(0.0310)	(0.0620)	(0.0494)	(0.0165)
	[0.0755]	[0.1657]	[0.0889]	[0.0527]
30+°C	0.2273^{*}	0.7195^{*}	0.2465	0.4222^{***}
	(0.0441)	(0.1150)	(0.0711)	(0.0688)
	[0.1012]	[0.2973]	[0.1843]	[0.1094]
Precipitation (mm)	-1.8950	-6.8090	-4.9512	-2.1175
	(0.4125)	(0.9943)	(0.7177)	(0.3253)
	[1.4849]	[4.4748]	[3.1452]	[1.2338]
Precipitation Sq	0.2418	0.8642	0.6173	0.2557
	(0.0589)	(0.1439)	(0.1039)	(0.0476)
	[0.2107]	[0.6410]	[0.4500]	[0.1835]
Observations	2,152	2,261	2,214	2,210
Counties	788	815	796	794
Years	3	3	3	3
Adj. R^2	0.344	0.415	0.277	0.458
Within R^2	0.106	0.215	0.147	0.322
RMSE	1.808	3.991	2.864	1.305

Notes: Reference category: 15-20°C. SE: () county, [] Conley (425 km).

Significance stars correspond to Conley SEs: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

All models were re-estimated excluding the 2012 year as a robustness check. 2012 was the dominant drought year by far. Thirteen of the sixteen primary coefficients remain statistically significant and there is no coefficient that changes sign. The result for the extreme heat bin (30+) remains unchanged in magnitude and significance which confirms that the income damage channel is not driven by the outlier year. The yield results are also robust with a very small attenuation in the extreme heat coefficient. This shows that 2012 contributes to the effect but does not dominantly determine it. The insurance results are more sensitive however. The Palmer Z-index RMA total coefficient falls to almost half per moderate to extreme drought pentad. The 30+ degrees Celsius bin now shows significant positive associations with the census insurance variable and the RMA total crop indemnity variable. However, the smaller magnitudes compared to the full sample's moderate to extreme drought variable still suggests that insurance responds to moisture extremes more than heat extremes. This reflects that 2012 was a very important year in the full-sample insurance results.

A.6 Acreage Response Models

Table A.19: Palmer Z-Index: Significant Acreage Responses (All Seasons)

	Log Acres			
	Corn		Soybeans	
	Planted	Harvested	Planted	Harvested
April-May (Planting Season)				
Mild Wet	-0.00507^{*}	–	–	–
	[0.00201]	–	–	–
Moderate to Extreme Wet	-0.00551^{**}	–	–	–
	[0.00211]	–	–	–
June-September (Growing Season)				
Moderate to Extreme Drought	–	-0.00950^{*}	-0.00308^{***}	-0.00513^{***}
	–	[0.00393]	[0.00075]	[0.00086]
Mild Drought	0.00374^{***}	–	–	–
	[0.00113]	–	–	–
Mild Wet	–	–	-0.00329^{***}	-0.00351^{***}
	–	–	[0.00070]	[0.00080]
Moderate to Extreme Wet	–	-0.00231^{*}	-0.00289^{*}	-0.00348^{**}
	–	[0.00092]	[0.00119]	[0.00129]
January-September (Extended Season)				
Moderate to Extreme Drought	–	-0.00701^{*}	-0.00265^{**}	-0.00426^{***}
	–	[0.00342]	[0.00091]	[0.00103]
Mild Drought	0.00242^{***}	0.00270^{**}	0.00285^{***}	0.00259^{***}
	[0.00072]	[0.00101]	[0.00072]	[0.00049]
Mild Wet	-0.00241^{*}	–	-0.00219^{*}	-0.00225^{*}
	[0.00110]	–	[0.00098]	[0.00099]
Observations	16,721	16,720	16,560	16,560
Counties	878	878	874	874
Years	22	22	22	22

Notes: Conley SEs (425 km) in brackets []. Significance stars: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.
Growing season models include flood controls.

Table A.20: Temperature Bin: Significant Acreage Responses (All Seasons)

	Log Acres			
	Corn		Soybeans	
	Planted	Harvested	Planted	Harvested
April-May (Planting Season)				
Days 20-25°C	-0.00245^{**}	-0.00264^{*}	–	–
	[0.00093]	[0.00103]	–	–
Days 25-30°C	–	–	-0.01056^{***}	-0.01135^{***}
	–	–	[0.00295]	[0.00280]
Days 30°C+	–	–	0.11691^{***}	0.11034^{***}
	–	–	[0.02432]	[0.02477]
June-September (Growing Season)				
Precipitation Sq	–	-0.00494^{*}	–	-0.00523^{*}
	–	[0.00252]	–	[0.00203]
January-September (Extended Season)				
Days 30°C+	–	-0.00828^{*}	–	–
	–	[0.00415]	–	–
Precipitation	–	0.10160^{*}	–	–
	–	[0.04890]	–	–
Precipitation Sq	–	-0.02056^{*}	–	–
	–	[0.00822]	–	–
Observations	16,897	16,896	16,740	16,740
Counties	887	887	883	883
Years	22	22	22	22

Notes: Conley SEs (425 km) in brackets []. Significance stars: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.
Reference category: 15-20°C.

Corn planting usually runs from mid April to late May, while soybean planting usually runs from early May to mid June. There is a stagger of two to four weeks, with significant overlap in May. Tables A.20 and A.21 show statistically significant acreage responses for both specifications and seasonal windows. It can be seen that Spring conditions significantly affect the area of corn planted - planting season mild wet and moderate to extreme wet conditions each are associated with reductions in corn planted acres by approximately 0.5 percent. No equivalent effect is found for soybean, which is consistent with its late planting window. Next, it can be seen that growing season moderate to extreme drought is associated with a reduction in corn harvested acres by 0.95 per cent but leaves corn planted acres unaffected. For soybeans, growing season drought is associated with reductions in both planted (-0.31%) and harvested (-0.51%) acres. Then, the temperature bin results for the April–May window reveal an anomalous positive association between extreme heat days (above 30 degrees Celsius) and soybean planted and harvested acres - +11.7% and +11.0% respectively - while days in the 25–30 degrees range reduce soybean planting by -1.06% and -1.14%. The positive extreme heat day effect is almost certainly a warm spring confound. It could be the case that years with anomalously high April-May temperatures above 30 degrees Celsius in the Midwest correspond to exceptionally warm springs that enable earlier and more extensive soybean planting. The extended season (January-September) results are broadly consistent with the growing season findings. Moderate to extreme drought is associated with reductions in both corn harvested and soybean planted and harvested acres, confirming that accumulated moisture deficits across the full pre-harvest period compound into meaningful acreage losses.

A.7 Yield, Income and Insurance Combined Models

Table A.21: Palmer Z-Index Combined Model: Yield Regressions

	Log Corn	Log Soy
Palmer Z-Index		
Moderate to Extreme Drought	-0.01252^{***} [0.00290]	-0.00862^{***} [0.00231]
Mild Drought	-0.00420^{**} [0.00152]	-0.00457^{**} [0.00171]
Mild Wet	-0.00373^{*} [0.00164]	-0.00250 [0.00180]
Moderate to Extreme Wet	-0.00925^{***} [0.00085]	-0.00660^{***} [0.00132]
Floods	-0.00137 [0.00109]	-0.00222^{**} [0.00081]
Temperature Bins (ref: 15-20°C)		
Below 10°C	-0.00076 [0.00514]	0.00176 [0.00460]
10-15°C	-0.00243 [0.00133]	-0.00441^{*} [0.00197]
20-25°C	0.00053 [0.00086]	-0.00040 [0.00069]
25-30°C	-0.00436^{**} [0.00135]	-0.00454^{***} [0.00072]
30°C+	-0.02725^{***} [0.00497]	-0.02368^{***} [0.00141]
Precip (mm)	0.05566^{*} [0.02598]	0.09744^{***} [0.01664]
Precip Sq	-0.00508 [0.00330]	-0.00910^{***} [0.00189]
Observations	16,620	16,460
Counties	873	869
Years	22	22
Adj. R^2	0.759	0.778
Within R^2	0.281	0.294
RMSE	0.140	0.128

Notes: Conley SEs (425 km) in brackets [].

Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Reference category: 15-20°C.

Table A.22: Palmer Z-Index Combined Model: Income Regressions

	Operations Income ($M)	Producers Income ($M)
Palmer Z-Index		
Moderate to Extreme Drought	0.15058	0.14663
	[0.13982]	[0.14972]
Mild Drought	0.48575	0.48696*
	[0.29544]	[0.20909]
Mild Wet	−0.25123	−0.17040
	[1.16444]	[0.87598]
Moderate to Extreme Wet	−0.24474	−0.05440
	[0.35067]	[0.35230]
Floods	−0.16886	−0.09077
	[0.30384]	[0.34059]
Temperature Bins (ref: 15-20°C)		
Below 10°C	−2.02040**	−1.81464**
	[0.74657]	[0.64372]
10-15°C	−0.64830*	−0.56914*
	[0.32000]	[0.25996]
20-25°C	0.11764	0.09271
	[0.18978]	[0.11865]
25-30°C	−0.64182*	−0.62065**
	[0.26093]	[0.20088]
30°C+	−2.17492***	−2.09862***
	[0.55504]	[0.41529]
Precipitation (mm)	−7.99486*	−6.71916*
	[3.16284]	[2.84323]
Precipitation Sq	1.03576***	0.82754**
	[0.28329]	[0.26026]
Observations	4,046	4,045
Counties	875	875
Years	5	5
Adj. R^2	0.763	0.781
Within R^2	0.069	0.091
RMSE	21.3	17.2

Notes: Conley SEs (425 km) in brackets []. Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Ref: 15-20°C.

Table A.23: Palmer Z-Index Combined Model: Insurance Regressions

	Census	RMA Total	RMA Corn	RMA Soy
Palmer Z-Index				
Moderate to Extreme Drought	0.26918***	0.78838***	0.69641***	0.09818**
	[0.03694]	[0.16413]	[0.15740]	[0.03687]
Mild Drought	−0.10546*	−0.24532	−0.28386*	0.01264
	[0.04592]	[0.15367]	[0.13038]	[0.04530]
Mild Wet	0.04642	0.22825	0.13796	0.01556
	[0.13281]	[0.36362]	[0.30331]	[0.05625]
Moderate to Extreme Wet	0.15053	0.29758	0.12030	0.09718
	[0.08922]	[0.21170]	[0.14834]	[0.05684]
Floods	0.07965	0.26814	0.13861	0.08782
	[0.09941]	[0.24995]	[0.21325]	[0.05341]
Temperature Bins (ref: 15-20°C)				
Below 10°C	−0.09277	−0.16535	−0.19881	−0.02677
	[0.09939]	[0.23101]	[0.17060]	[0.11894]
10-15°C	0.05634	0.05367	−0.00349	0.05739
	[0.06818]	[0.15362]	[0.10600]	[0.04655]
20-25°C	−0.07272*	−0.29541**	−0.26155**	−0.03507
	[0.03630]	[0.09939]	[0.08333]	[0.03330]
25-30°C	0.09981	0.23405**	0.13043*	0.06981
	[0.06201]	[0.08775]	[0.05856]	[0.04121]
30°C+	0.17436	0.38057	0.17393	0.19355*
	[0.18049]	[0.40822]	[0.33576]	[0.07796]
Precipitation (mm)	−1.55233	−2.68521	−0.72779	−1.78947*
	[1.15633]	[3.48203]	[3.05883]	[0.91159]
Precipitation Sq	0.19413	0.36037	0.12203	0.21694
	[0.16095]	[0.42625]	[0.36479]	[0.12842]
Observations	3,028	3,170	3,091	3,073
Counties	849	874	849	841
Years	4	4	4	4
Adj. R^2	0.474	0.460	0.426	0.481
Within R^2	0.205	0.237	0.203	0.261
RMSE	2.904	7.576	6.622	1.588

Notes: Conley SEs (425 km) in brackets [].

Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$. Ref: 15-20°C.

A.8 Producer Income Results

Table A.24: Producer Income Regressions: Palmer Z-Index

	Producers Income ($M)
Moderate to Extreme Drought	-0.3317
	(0.0977)
	$[0.2735]$
Mild Drought	0.4026
	(0.1226)
	$[0.3817]$
Mild Wet	-0.6192
	(0.2913)
	$[0.6156]$
Moderate to Extreme Wet	-0.2385^{**}
	(0.1810)
	$[0.0820]$
Floods	0.2214
	(0.2482)
	$[0.1480]$
Observations	4,045
Counties	875
Years	5
Adj. R^2	0.763
Within R^2	0.011
RMSE	17.9

Notes: SE: () county, [] Conley (425 km). Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.

Table A.25: Producer Income Regressions: Temperature Bins

	Producers Income ($M)
Below 10°C	-1.7123^{**}
	(0.3699)
	[0.5951]
10-15°C	-0.5935^{*}
	(0.1649)
	[0.2790]
20-25°C	0.1063
	(0.0718)
	[0.1108]
25-30°C	-0.5659^{**}
	(0.0963)
	[0.1770]
30°C+	-1.9843^{***}
	(0.1602)
	[0.3926]
Precipitation (mm)	-8.5399^{**}
	(1.6312)
	[2.4564]
Precipitation Sq	0.8858^{**}
	(0.2331)
	[0.3431]
Observations	4,112
Counties	889
Years	5
Adj. R^2	0.780
Within R^2	0.084
RMSE	17.3

Notes: Reference category: 15-20°C. SE: () county, [] Conley (425 km).

Significance: $^{***}p < 0.001$, $^{**}p < 0.01$, $^{*}p < 0.05$.