DROUGHT INDEX-BASED INSURANCE FOR THE US CATTLE RANCHING INDUSTRY

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Drought Index-Based Insurance for the US Cattle Ranching Industry

Thesis directed by Professor William R. Travis

The recent availability of federally-subsidized rainfall-index insurance for US grazing livestock producers provides a previously absent level of financial support that has long been common in the crop production industry. This development is important for the economic well-being of the small-scale rancher who faces the ever-present risk of drought. When drought hits the ranch, forage-production is reduced, expensive supplementary feed becomes necessary, and often the rancher must sell cattle into a flooded local market. In recent years, particularly severe national-scale droughts have caused large economic losses for agricultural producers, renewing interest in drought risks mitigation strategies. Over these years, weather-based index insurance has become increasingly popular for the mitigation of such risks because it is designed to avoid many of the pitfalls that make loss-based insurance inefficient. By basing loss on an indicator and not experienced loss, expenses associated with profit-seeking behavior by policyholders can be significantly reduced. This feature promises to lessen operation costs, decrease premiums, and expand possible coverage to a larger number of people, but will only be effective to the degree that the index accurately indicates loss. The Pasture, Rangeland, and Forage (PRF) rainfall-index insurance program assumes that rainfall is highly correlated with the rangeland forage. However, cumulative rainfall is only one factor of many that determines rangeland health, creating a risk of non-payment. The existence of a myriad of drought indices specifically designed to monitor the impacts of drought begs the question; why not indicate drought-induced loss with a drought index? A drought index would provide the same efficiencies as the rainfall index while potentially reducing the risk of non-payment when there are losses. In this study, various drought indices are assessed for their ability to indicate the economic impacts of drought in the US live-cattle market, and subsequently tested as experimental alternatives to the rainfall index in the PRF. The results demonstrate that they explain similar amounts of variance in cattle weights at live-auctions as the rainfall index but incentivize appropriate growing season protection and have the potential to significantly reduce the chances of missed payouts during drought without creating actuarially unmanageable payout patterns.

DEDICATION

This master's degree would not be possible without the generous assistance and guidance of a particular *professor* from Illinois. I, therefore, dedicate this thesis to Dr. Rachel Cook who gave me my first chance in academic research, alerted me to the possibility of continued education, and who's recommendations were critical to my acceptance into this school. She has changed my life and I will be forever grateful.

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CHAPTER I

INTRODUCTION

The US cattle ranching industry has historically received significantly less governmental assistance when dealing with drought than the US crop production industry. While subsidized crop insurance has been available since 1980, such protection has been minimal for ranchers as governmental drought relief is made, primarily, only in response to each disaster. Considering the droughts of the 21st century and projections of increased dryness in many cattle producing regions of the US, the strategies involved with drought hazard management on the range must improve in order to maintain the economic well-being of ranching communities. Where more general, reactive, and less targeted hazard mitigation efforts have sufficed, these strategies must use the most appropriate social and climate information available with proactive implementation plans designed to minimize risk *and* expand protection across a wider demographic of people. This need is particularly reflected in the effort to reduce uncertainties involved with weather-based index insurance programs that are becoming increasingly popular world-wide as a means of dealing with pastoral drought risks.

Weather-based index insurance products base their payouts on an indicator of a weather variable that is assumed to represent the condition of the insured item. Payouts are given only if the observed index value falls below a certain percentage of average historical values for that location and time, avoiding the need to prove loss and circumventing many of the inefficiencies in traditional loss-based plans. By avoiding the need to prove loss the use of an index reduces operating costs on the part of the insurer which lessens the premium payments for the insured, expanding the affordability of insurance to a larger portion of a population. Additionally, a properly chosen index will be independent from the influence of the policyholder and this disincentives behavior that increases the chance of payout, an issue common in loss-based insurance and referred to as moral hazard. An independent index will also reduce information discrepancies between the insured and insurer, as it is the insurer that provides the information. In an insurance setting the presence of such a discrepancy is a problem that will most typically manifest as a tendency of higher risk populations to purchase more policies than lower risk groups, a tendency referred to as adverse selection. The minimization of moral hazard and adverse selection can further reduce operation costs, increase financial efficiency, and expand potential coverage.

The main drawback of this type of insurance, though, is the difficulty of correlating the index with experienced losses, known as basis risk in the index insurance literature. A poorly correlated index will often fail to pay following harm or might pay when there is none, leaving reception of payment partly up to chance. An insurance plan that fails to indemnify is obviously a problem, but it will also lead to poor participation rates and relatively high participation rates are vital for an effective risk-sharing program. Where this is not true government subsidization, lowered deductibles, and other strategies must be used to incentivize uptake. While a policyholder might not consider an undue payment to be a problem at first, if it is common enough it will increase provider costs which will eventually be reflected in the premiums they have to pay.

The efficacy of any index insurance program to efficiently mitigate loss is dependent on the ability of the index to accurately reflect experienced loss. In the case of drought mitigation in ranching and agriculture, research indicates that cumulative rainfall, for example, is alone a poor indicator of plant production. Because of this a good deal of creative effort has been put into the development of rainfall-index variants that improve the correlation between cumulative rainfall and production loss in agriculture. A lot of effort has also been put into the development of drought indices to do the same. Drought indices such as the Palmer Drought Severity Index or the Standardized Precipitation-Evaporation Index are designed specifically to capture the impacts of a drought. Recognizing the influence of factors such as evapotranspiration and drought duration on water deficiencies, they seek to identify sources of both water inputs and losses to more fully describe water shortages in a system. Also, agriculture is often the primary consideration of these index developers as it is heavily dependent on the rainfall and is usually the hardest hit sector. Indeed, it was drought effects on soil moisture and its importance to farmers that motivated early quantifications of drought by Wayne C. Palmer in the 1960s. Despite this apparent utility, there has been no significant research into the efficacy of existing drought indices in an agricultural insurance setting. So, considering the issue of basis risk and the limitation of rainfall-index insurance for targeted drought mitigation, the efficacy of a well-chosen drought index as a basis for loss in weather-based index insurance is examined here.

Recently, ranchers have gained access to a variant of crop insurance in the form of a rainfall-based index program called Pasture, Rangeland, and Forage (PRF). In August of 2015 the PRF completed an eight-year experimental pilot stage and was made available to every county of the contiguous United States. With it, ranchers have the option to buy a policy, tailor its specifications to their land and local climate, and potentially receive compensation for added feed costs and lost revenues due to drought. Since 2007 its uptake has been steadily increasing (Figure 2), and because it is heavily subsidized it is certain to provide financial support to participants. However, can rainfall accurately indicate losses in the cattle ranching industry and will the PRF provide drought relief reliably during the growing season when it is most needed? If not, would a drought index designed specifically to indicate the impacts of drought result in more appropriate payments? Would it even be actuarially feasible to use a drought index in an insurance application, or would the resulting payouts exhibit unreasonable qualities?

This study addresses these questions by comparing rainfall and drought indices using an econometric analysis and a simulation of hypothetical insurance plans. Various drought indices are chosen for analysis based on their probable utility in quantifying agricultural drought conditions across the rangelands of the United States and assessed for their ability to indicate economic losses in the cattle production industry. They are then used as experimental alternate indices within the structure of the PRF to test for feasibility of use and comparison of results with potential payouts from the rainfall index. The hypotheses tested in this study are that the use of a well-chosen drought index would reduce basis risk by providing more accurate indications of economic losses in ranching, and that the use of a drought index in an insurance setting would serve as an improvement over the effectiveness of a rainfall index-based program by generating more appropriately timed payouts. It is also hypothesized that this type of index could be implemented in an insurance setting without causing significant actuarial imbalances.

Chapter one examines ranching vulnerability to drought and summarizes historical federal involvement in the industry to underscore the importance of efficient state-sponsored drought mitigation strategies. Chapter two provides a description of each drought index used in the analyses which follow. Chapter three describes an econometric analysis performed to quantify the ability of the rainfall and various drought indices to indicate drought impacts in the live-cattle market. Finally, chapter four describes the results of a simulation of insurance payments using each drought index as an experimental alternative to the rainfall index in the Pasture, Rangeland, and Forage insurance plan. In this final project, special attention is given to the seasonality of resulting potential insurance payments.

Cattle Ranching Vulnerability

Cattle ranching in the US, as a form of dryland agriculture that is fully reliant on the weather, has always operated with significant climate risk. Decisions about stocking rates, feed purchases, grazing leases, the timing of sale and calf weaning, etc., depend largely on whether or not enough precipitation is expected to maintain normal forage levels on the range and in supplementary feed operations (Shrum et al, 2018). In most areas of the US if sufficient rain has not fallen by a critical growing season month, ranch managers must adjust their plans to account for inevitable shortages and added costs. If full-fledged drought conditions manifest, supplementary feed costs will rise as demand spikes and there will be a rush to sell cattle which floods the market causing prices and revenues to fall (Countryman et al, 2016). Ranchers may have to sell off significant portions of their stock and, after the drought ceases, they will have a difficult time rebuilding their inventory with similar quality animals as the market price rebounds (Dunn et al, 2005). They must also be very careful about how quickly they restock because a drought-stressed range is more vulnerable to grazing pressure and long-term damage to forage productivity, especially following multi-year events (Griffin-Nolan et al, 2018). Historically, conservative stocking rates, adaptive management strategies, the mobility afforded by the market, and emergency government aid have helped the industry to survive these situations. However, for small-scale ranching businesses, the margin between profit and loss is often perilously close while particularly widespread and severe droughts have demonstrated limits to the effectiveness associated with these strategies (Countryman et al, 2016).

21st Century Drought

While drought in the United States is not uncommon, recent iterations of the phenomenon appear to be particularly prolonged and severe. Early 21st century droughts in the US are already ranked among the most severe that the nation has ever experienced. By the end of July 2002, 49% of the country was reported as being in moderate to extreme drought with major cattle production areas in the central states being hit the hardest according to the Palmer Drought Index (NOAA, 2002a). The Weekly Weather and Crop Bulletin categorized much of the range and pasture land conditions in these states as poor to very poor. Colorado was cited as having the most widespread impact with 92% of land in this category, while Arizona and Nebraska followed closely at 87% (NOAA, 2002b). A drought in Texas in 2011 set Texan records for high temperatures, low precipitation, and single-year costs to agriculture, causing $7.62 billion dollars in losses (Guerrero et al, 2012). Texas livestock and hay production were hit hardest with combined losses of roughly $4

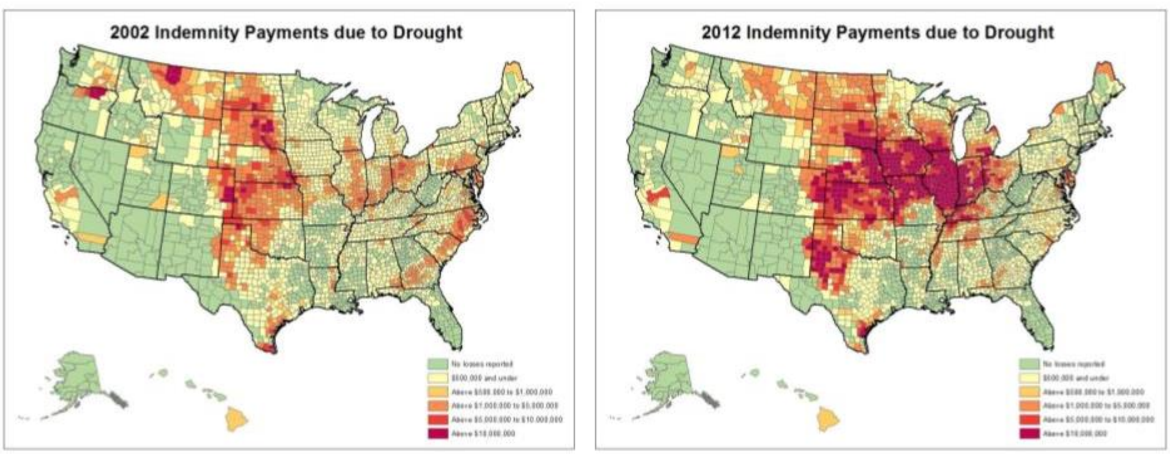

Figure 1. *Risk Management Agency total indemnity distributions due to drought-induced losses in 2002 and 2012. Source: http://drought.unl.edu/Planning/Impacts/DroughtIndemnityMaps.aspx. (USDA-RMA, 2018a)*

billion. During the drought of 2012 the USDA declared 2,245 counties covering over 70% of the entire country as disaster areas making all farm and ranch operators within this area eligible for emergency loans at interest reduced even further than the already low emergency rates. Over the course of this event a suite of emergency measures was enacted, including the allowance of 2.8 million acres of Conservation Reserve Program land for haying and grazing and the distribution of $200 million worth of forage and feed (USDA, 2013). By January 1st, 2013 the national inventory of cattle reached 89.1 million, the lowest number since 1952 (USDA-NASS, 2013).

In a comparison of Palmer Drought Severity Index values between this drought and those of other national-scale droughts in the 1930s and 50s, Heim (2017) found that the peak 2012 drought extent, 64.5% of the contiguous US in moderate to exceptional drought categories, had not been seen since 1940 when the value was matched and was only exceeded by a peak value in July 1934 of 78.8%. The entire period between 2000 and 2014 was found to be comparable with these decades in terms of drought extent, severity, and duration. Importantly, this author notes that precipitation deficiencies in 2012 were not nearly as severe, attributing most of the intensity of this event to elevated temperatures.

An increasingly common theme in the drought research literature is the possibility that, as temperatures and evaporation rates rise, normal or increased levels of precipitation will mask experienced drought. Easterling et al (2007) examine this by comparing time-series of Palmer Drought Severity Index values throughout the contiguous US derived from both unaltered and detrended precipitation and temperature datasets. Areas in severe or extreme drought according to the unaltered and detrended PDSI for the contiguous US and individual regions were compared. The years between 1950 and 2006 were used because a slight warming trend began in the 1950s before more significant increases began in the 1980s, while much of the US experienced a concomitant rise in precipitation. They found that significantly smaller portions of the US would have experienced severe to extreme PDSI values using detrended temperatures than was true using the observed temperature data, while the opposite was true when precipitation was detrended. Regionally, the differences between observed and detrended temperature were generally found to be more significant at northern latitudes. This finding has obvious implications for the utility of rainfall-based indices over-time, but also for parts of the US that are projected to experience increased levels of rainfall and where the effects of drought may go unrecognized. It is the increasing occurrence of these temperature-driven droughts that motivated the innovative new Evaporative-Demand Drought Index (EDDI), which uniquely categorizes drought without the input of precipitation.

For the more southern and central regions of the US, climate projections indicate a high potential for increased drought that would be apparent without considering this masking effect (Cook et al, 2015). This is particularly concerning for the livestock industry as both forage availability and animal health will be affected by added heat in some of the most active cattle production areas (Nardone et al, 2010). Significant uncertainty surrounds these predictions; as Hoerling et al (2012) summarize, some studies suggest the likelihood of a full climate regime shift towards quasi-permanent aridity (Burke et al, 2006; Dai, 2013) while others are more tempered, suggesting moderately drier scenarios (Sheffield and Wood, 2008, Winter and Eltahir, 2011). However, studies generally agree that, to some degree or another, dry conditions are most likely to increase for many central and southwestern US areas. In addition, and regardless of the effect of warming trends, paleoclimatic studies are uncovering the existence of historical multi-decadal drought, indicating the possibility of a long-term cycle that could return to the US, regardless of climate forcing.

While there is no doubt that the early 21st century has experienced severe drought, these may pale in comparison to cyclical-multidecadal events detected at many points in history and pre-history. Research has uncovered tree ring evidence for these ancient drought events in the Southwest and Central Plains (Cook et al. 2014). Alarmingly, Herweijer et al. (2007), using a 1,000-year model of a gridded network of tree ring data, find that drought events as long 40 years were common during the medieval period of history (900 to 1400 AD) and associates these with protracted El Niño-Southern (ENSO) Oscillation patterns that were similar to the sorts we have observed in recent years (Herweijer et al., 2007). These historical drought events were found to be similar in spatial extent and severity to their modern counterparts. Another study compares paleoclimatic recreations of drought in Southern California to that which began in 2011 and, in terms of severity, ranks it as similar to or worse than the most intense droughts in the last 1,200 years in that area (Griffin and Anchukaitis, 2014). Research will often point to global warming as a major contributing factor to the exacerbation of these recent drought events, however this research reveals that the causality of the hazard is not so simple; the possibility of long-term drought has always been present in North America. Because of this, risk management agencies need to be as prepared as possible should this possibility manifest and overwhelm current response systems.

Economic Hardship

Drought is not the only challenge that US ranch managers face; decisions are also made in a decreasingly amiable economic climate. Ranching is not an overly profitable industry; many small ranch owners who are able to stay in the industry must take on second jobs and face a constant pressure to subdivide and sell their land to developers to make ends meet (Rowley, 2008). Also, cattle producers are in a losing battle over market power with the beef packing industry that has a heavy influence over cattle prices and subsequent revenues. Crespi et al (2010) note a dramatic progression of market domination by large firms of that industry; the market share of the top four heifer and steer meat-packing firms increased from 25% in 1976 to 80% in 2007. In a more recent statistical analysis, Panagiotou and Stavrakoudis (2017) find that the net marginal product of cattle production, or the increase in production that can be expected with additional inputs, is 23% lower than the current price of cattle can support, and that this discrepancy is primarily due to imbalances in marketing power, corroborating Crespi et al. Additionally, Starrs (2000) refers to a similar situation as the "Wal-Mart Dilemma", where, increasingly, competition from large cattle ranching operations force smaller ranches out of business.

This underlying economic situation is important for the analysis into the effectiveness of weather-based insurance because it reveals there are multiple sources of vulnerability in the US ranching community and, more saliently, because the livelihood of an entire, and iconic, group of American people appears to be threatened.

Government Involvement in Ranching

The development of the PRF represents a novel form of governmental assistance for the ranching community, but is only the most recent in a long series of interventions deemed necessary following historical damage due to drought and overgrazing. While the passage of the Taylor Grazing and Soil Conservation Acts of the 1930s would ultimately intertwine the government into rangeland management practice to rescue the American grassland from human mismanagement, drought-risk management interventions have traditionally been reactionary and marked by large sums of emergency financial assistance and low interest loans for disaster relief as approved on a case by case basis in Congress.

19th to 20th Century Drought

In the 1850s, eastern settlers brought cattle production to the West, whose climate and vegetation were largely unfamiliar and which was experiencing an uncharacteristic, but timely, wet spell (Wilhite and Wood, 2001). Ranching in the Western U.S. by the latter half of the 19th century was characterized by the dominance of wealthy land owning “cattle kings”, ever-expanding numbers of livestock, and plowing and fencing of the range. During these early years the livestock industry was booming and massive profits were being made via heavy unregulated grazing of the open range. When this was coupled with the rancher’s relative inexperience in western climate, the industry was left highly vulnerable to inevitable droughts and large-scale cattle die-offs (Rowley, 2008).

Bahre and Shelton (1996) give a history of rangeland destruction due to drought and overgrazing in 19th century Arizona, and this is illustrative of the situation. A severe drought of 1885 in the Southwest withheld 50% of normal annual precipitation in some locations and lead to large cattle losses, though precise numbers are not available. According to the authors, this served as an early indicator of climate vulnerability, but it did not spur any detectable change in national policy. Precipitation during another drought between 1891 and 1893 was actually 70% of normal, roughly, but the duration was much longer than in 1885 and rangeland stocking rates were much higher leading to even heavier losses. An estimated average of 50% of reported livestock were lost. Around the same time, severe Great Plains winters in 1879, 1886, 1889, and 1890 killed large numbers of cattle, putting many out of business (Rowley, 2008). Each of these winters followed severe droughts that reduced forage and set the stage for the die-offs (Mock, 1991). Rowley notes the importance of this last year, 1890, to policy changes concerning the cattle industry. These events, with a concomitant rise in conservation ethic, lead to the Forest Reserve Act of 1891 which placed a large amount of previously open land under the protection of the government and off limits to cattle production, though permits would later allow grazing there.

Back in Arizona, an 1898-1904 drought brought 74% of normal precipitation, this time spread over a 6-year period, and a reported average of 25% of stock were lost. 1924, following a 20-year period of plentiful rainfall, brought what would be the worst single-year meteorological drought event on record until 1994, with large die-offs reported by the summer of 1925. Finally, the 1933-34 dust bowl arrived in the central US and this is described as the last large-scale die-off due to drought in Arizona (Bahre and Shelton, 1996).

In May 1934 the US government's Agricultural Adjustment Administration (AAA) created a $100 million program administered by the new Drought Relief Service (DRS) to move cattle out of the area (Lambert, 2018). By the end of the year about 8 million cows would be purchased by the DRS and either moved out of drought-stricken areas, sent to slaughterhouses, or exterminated as unfit for consumption (Bahre and Shelton, 1996; McConnell and Smith, 2015). In the spring of that year the Soil Conservation Service would begin federal regulation of private land (Rowley, 2008) and a few months later the Taylor Grazing Act would famously end the open range on public lands, marking the beginning of heavy federal involvement in the cattle industry (Ross, 1984).

The Taylor grazing act

In 1934, President Franklin D. Roosevelt signed the act into law creating the Division of Grazing to manage the open rangelands. Ross (1984) provides a thorough history of the program after 50 years of operation which is summarized here. The program started out as a relatively small operation, limited to only 80 million acres in the first year, but it would grow significantly; up to 142 million in 1936 and then in 1954 the acreage limit was lifted entirely. Early in the program's development the conservation ethic that served as the original foundation of the act was significantly undermined. WWII shifted priorities towards production and grazing pressure increased with emergency war licenses, construction of access roads, and a reassessment of the importance of "wildlife forage". Additionally, the Grazing Service, which was the updated name of the Division of Grazing, was understaffed during the whole affair. In 1945 Congress disagreed with the Grazing Service over grazing fees which lead to a halving of the service's budget, after which it was merged with the General Land Office and the Bureau of Land Management (BLM) was formed. This is when public grazing lands fell into the Department of the Interior's jurisdiction.

Grazing fees were continually increased until the BLM's rangeland management restoration plans began to show success and by 1949 state advisory boards were formed to help determine appropriate local stocking rates. This also shifted the governing tendencies of rangeland management away from a single- to multi-use purpose, as minerals, forests and other resources fell under the BLM's authority. Rangeland conditions would improve after this, though not as much as was possible so, in 1974, the National Environmental Policy Act required the BLM to generate 144 environmental statements for 170 million acres of land by 1988. In 1976 the Federal Land Policy and Management Act required the government to practice multiple-use and sustained yield and allow full public participation. Then, in 1978, via the Public Rangelands Improvement Act (PRIA), it was made clear that the rangelands were still in poor condition, would be so until more funding was put towards them, and that severe environmental and economic damage would ensue if this was not done. This lead the BLM to establish many programs geared towards cooperation, stewardship, organized planning, and innovation. Also, the PRIA updated the fee calculation to take into account beef production costs, market prices, and grazing fees on private lands (Ross, 1984).

The Taylor Grazing Act is symbolic of the intervention of the US government in the livestock grazing industry, though it was only one of many actions taken in response to the great droughts of the 1930s. These impositions were often met with considerable reluctance. For example, the federal cattle purchase program of 1934-35, though welcomed by many struggling ranchers, was seen as an unfair infringement on property rights by others. The program was voluntary, and it was incredibly difficult to sell weakened cows privately at the time, but this could not overshadow the frustration producers felt at the intrusion and their fears of dictator-like federal control; it was uncertain whether the program was intended to be a temporary emergency measure, or a long-term management strategy (Lambert, 2018). It is interesting to note Ross' assessment of the limitations of the original grazing act. According to him it was originally perceived as a "Rancher's public land law" that only served the cattle industry of the West. There was a sentiment among both Congress and the public that all federal control of grazing land was only temporary until it became private or was allocated for other "special uses". Lambert corroborates the presence of such a sentiment, quoting a 1935 article in the American Cattle Producer:

> "The National Live Stock Association passed a resolution commending the purchases and praising the government for its help to the industry. But the cattlemen seemed to feel that, now that the government had saved the industry, the government could go its way and leave the cattlemen alone." (The American Cattle Producer, 1935)

Today, state and federal governments are intricately involved in the entire cattle production process and the reactions to measures taken following the federal acts of the 1930s are echoed in modern ranching sentiments of distrust in the government (Rowley, 2008). This highlights an important consideration to make when assessing the PRF and this study's choice of an alternative index: failure to indemnify may not be met with much understanding. As Smith and Watts (2009) point out, the sustainability of any agricultural insurance program depends on the willingness of farmers to participate, a willingness that could quickly erode in an already wary US ranching industry if this failure occurs too often.

20th and 21st Century Disaster Relief:

Though the effectiveness of rangeland conservation programs has waxed and waned as a rotating congress and public sentiment drive uncoordinated policy changes, the conservation ethic that motivated the original Grazing and Soil Conservation Acts is still present to some degree. However, despite a gradual transition in fair-weather management policy, the progression of drought disaster policies has not kept pace.

Prior to the droughts of the 1950s, excepting certain events such as the droughts of the 1930s, the US government's involvement in disaster relief was minimal and financial aid was seen as outside the purview of its mandate. Federal assistance came, mostly, in the form of non-financial aid and was authorized in response to specific disasters (Barnett, 1999; Wilhite and Wood, 2001). In 1949, though, the Farm Services Agency (FSA) was created specifically to administer natural disaster relief loans at low interest rates to farmers and ranchers. The Disaster Relief Act of 1950 would also establish a general authorization for congressional aid in advance of any particular disaster, though event-specific legislative aid would continue (Barnett, 1999) and from the 1950s to 1970s the US government's contribution towards such relief efforts would increase from only 1% to over 70% (Clary, 1985). As a particularly expensive example, drought-specific aid from 1974 to 1977 was estimated to cost a total of somewhere between \$7 and \$8 billion (Wilhite et al, 1984). Even after the creation of the Federal Crop Insurance Program, from 1980 to the mid-1990s about \$13.5 billion of cash payments were made with about \$4 billion of that due a drought in 1988 alone, and these were in addition to emergency loans (Barnett, 1999).

21st Century Livestock Assistance

Today, the FSA is still the main governmental organization responsible for relief to agricultural producers following natural disasters, and it has several programs designed specifically for livestock producers (FSA, 2017). The Livestock Indemnity Program (LIP) indemnifies livestock mortality due to abnormal and extreme weather events (including earthquakes and volcanic ash), disease outbreaks due to adverse weather conditions, or predation from federally reintroduced carnivorous species. The FSA reimburses the livestock owners 75% of the current market value of the animal, unless they are contract producers in which case they are compensated 75% of the estimated lost revenue due to the loss.

The Emergency Assistance for Livestock, Honey Bees, and Farm-raised Fish (ELAP) allocates 20 million dollars of the Commodity Credit Corporation budget to assist in certain losses that are not covered by other emergency programs authorized in the farm bill (2014). These losses include livestock mortality, feed, and grazing losses due to hazards other than drought and wildfires. It also provides assistance for water transportation costs in the case of drought, costs of treatment for cattle with tick fever as well as, honeybee and farm-raised fish feed and mortality. Payments from this program will come at a reduced rate for instances where the total demand for funding exceeds \$20 million.

The Livestock Forage Disaster Program (LFP) uses the U.S. Drought Monitor (USDM) (Svoboda et al, 2002) to trigger relief payments for producers with added feed costs from drought and loss of access to rangeland due to fire. The USDM is considered the operational standard drought-monitoring tool for the US and categorizes drought severity on a weekly basis (Hobbins et al, 2016). Monthly payments depend on county eligibility, and the duration and severity of USDM drought classifications during the grazing season. Monthly payments are equal to whichever is less; 60% of the feed costs of the livestock themselves or the feed costs required to compensate for 60% of the calculated carrying capacity of the land. In the case of lost revenue from drought induced livestock sales during the previous two years, 80% of the monthly payment is given. Lost grazing access due to fire results in 50% of the monthly payout, for a period of up to 180 days.

Assistance from any of the above FSA programs have two main limitations. The first is a cap on the total amount a producer can receive from all three: $125,000. The second limits eligibility based on income; adjusted gross incomes over $900,000 are ineligible.

Dunn et al note that one effect of financial relief to the cattle ranching industry has been to encourage continued grazing of rangelands when drought stress would otherwise warrant significant reductions of stocking rates. While such relief may be necessary to maintain the cattle production industry, particularly in the semi-arid West, as Wilhite and Wood (2001), Rowley (2008), and many other researchers argue, governmental drought relief in US cattle production has been largely reactive which, in addition to encouraging maladaptive rangeland management, generates uncertainties for producers and significant financial inefficiencies for the government. Each of these authors echo calls for more proactive drought relief policies that have been made since the 1980s. These calls appear to be influencing policy somewhat as is indicated by the more recent development of two insurance-based loss mitigation programs (in addition to the PRF) that are provided through the Risk Management Agency (RMA, 2017b).

The Livestock Risk Protection (LRP) program is a price-protection product similar to the rainfall-index program; if the price falls below a chosen percentage of an expected ending value a payout is given to the policyholder. It is available for 38 states, and for calves, steers, heifers, Brahman, and dairy cattle between 600 and 900 lbs. The livestock Gross Margin (LGM) is similar to the LRP, but takes feed costs into account. Using estimated future prices, this program calculates the difference between expected revenue from selling finished cattle and expected costs from feed. The indemnity is then paid based on the difference between the expected and realized prices.

Difficulties with Multi-peril Insurance

Insurance was a major part of US crop production long before the Federal Crop Insurance Act of 1980. In an effort to allay the effects of crop price depressions and shift some of the burden of natural disaster relief to the public sector, the original Federal Crop Insurance Act was passed in 1938 and the Federal Crop Insurance Program (FCIP) was formed following years of effort in congress and state-sponsored research into its operability. By this time several private US companies had attempted and failed to create and maintain a multi-peril crop insurance product, while, as Kramer (1983) claims, no other government in the world had been able to manage it either, leaving the US government with very little experience or precedent to fall back on. The Federal Crop Insurance Corporation (FCIC) was created to manage the program with a $100 million budget. Originally, the program was geared towards wheat production insuring farmers for either 50 or 75% of their average yield while premiums were calculated as a weighted average of their individual and county-wide losses. Major droughts, lack of precise yield data, low levels of participation, and adverse selection led to unmanageable loss ratios and a loss of congressional support in 1943. However, major amendments to the Act in 1948 revived the program and, though severely limiting its availability, gave it a wide mandate for experimentation. Experimental programs would continue with mixed success until the late 1970s when the Carter Administration convinced Congress to lift the availability limits entirely and expand coverage to all agricultural commodities with sufficient data to set actuarial rates (Kramer, 1983).

In 1980, after what was effectively a 42-year pilot phase, the new Federal Crop Insurance Act made FCIP coverage nationally available and the Multi-Peril Crop Insurance (MPCI) program was established to replace an experimental analog that had been in place since 1973. This insurance program would protect against crop losses due to any cause, including hurricanes, tornadoes, flooding, and drought. With this new program insurance payouts were triggered by yield deficits and payments were determined by market price, while price guarantees were also available. If a policyholder's yields were determined to be under a certain percentage of normal production, or insured yield, the policyholder was compensated according to the amount of yield deficit and the current crop price (Knight and Coble, 1997). Subsidies and administrative costs would be provided by the Federal Crop Insurance Corporation (FCIC) while private companies would provide insurance plans. The program was originally intended to be actuarially sound with little financial input from the government (Miranda, 1991).

Early in the program, three insurance yield levels were available as payment triggers; 50, 65, and 75%. Before 1980, yields were based on countywide areal yield measurements, but a provision in the 1980 act allowed for more specified individual farm-based policies and farmers with 3 or more years of production data could choose to be compensated directly for their specific production deficits. This was quickly updated with a method that based insured yield levels on individual farm production history for policyholders with at least 10 years of yield data (called the Approved/Actual Production History or APH). Those without a 10-year record defaulted to the county-based yield history (Knight and Coble, 1997).

Premiums were originally subsidized by 30% to encourage participation in the program. Participation rates did rise following the 1980 bill, but would remain relatively low (~38%) until significant reforms began in 1994. In 1987 Congress started to vote for frequent, provisional disaster bills to compensate unprotected farmers. These were passed yearly until 1994 and often required participation in the MPCI program for reception of aid to improve program uptake. By 1994 the cumulative unsubsidized loss ratio (indemnities paid to premiums received) was 1.41, well over the target loss ratio of 1.0 with a roughly $3.3 billion gap between payouts and premiums. This, in combination with continued low participation prompted redesign in 1995. This redesign punished individual farms with particularly low yield histories, began to push county-based yield products to minimize moral hazard and adverse selection, and mandated participation in the MCPI as a requirement to participate in other assistance programs (Knight and Coble, 1997).

Catastrophic insurance plans were also made available in 1995 as alternative minimum requirements for other assistance programs. These provided 100% subsidies and more complete loss compensation in exchange for added processing fees. This helped to increase participation in the program, but further contributed to the large expansion of the program's liability: $13.5 billion in 1994 and $25.2 billion in 1995. In 1996 farmers were allowed to opt out of the MPCI or catastrophic coverage as a requirement for other programs and the more common revenue-based insurance plans of today were launched as pilot-programs (Knight and Coble, 1997). These efforts would lead to significantly improved participation rates; by 2008 participation reached 80% of eligible US farm land and this would actually prompt other countries to adopt much of the structure of the FCIP. However, the incentives required to encourage this rate are very costly; by 2013, total FCIP liability would balloon to $114 billion with subsidies upwards of 60% and annual payments reaching $10 billion (Goodwin and Smith, 2013).

Why has the Federal Crop Insurance Program been so expensive? Barnett (1999) explains that the fundamental difficulty of a disaster-oriented insurance plan is one of positively correlated risk. In a disaster, large groups of policyholders will receive payouts at once, so payouts will be highly correlated while the probability of any one disaster is difficult to discern. For small-scale accident protection more common in private insurance, individuals will receive payouts in a much more random pattern, meaning they are relatively uncorrelated, and when these individual payments add up over time the probability of their occurrence typically becomes clear enough to allow for a proper assessment of the risk involved. The difference between positively correlated and uncorrelated risk is also referred to as the difference between systemic and independent risk (Zeuli and Skees, 2005) and is often used to describe the hazards insured by the FCIP (Miranda and Glauber, 1997; Goodwin and Mahul, 2004). When this systemic risk is present, reinsurance and other methods of spreading the risk across a wider number of people can be used, but if it is too high governments must compensate for the discrepancy, usually in the form of a premium subsidy.

As Goodwin and Mahul (2004) observe, it is rare to find a publicly provided multi-peril product that can survive without large government subsidization. Earlier, Wright and Hewitt (1994) claimed that there were no successful private ventures into the practice, and this is largely due to systemic risk. Miranda and Glauber (1997) consider this to be the primary impediment to crop insurance efforts and build a stochastic model of US crop insurance indemnities which estimates that systemic risk generates 20 to 50 times the costs that would occur if farm losses were fully independent. Wright and Hewitt (1994) explain that multi-peril insurance mechanisms ultimately fail due to a suite of behavioral factors, in addition to systemic risk. These include adverse selection along with both production and finance-oriented mismanagement from moral hazard induced by subsidization as farmers are incentivized to abandon traditional forms of risk management in favor of a reliance on insurance. Problems from these advantage-seeking behaviors can run even deeper than the definition would suggest. For instance, Hayde and Vercammen (1997) find that there is more financial loss from dishonest yield reporting in agricultural insurance than from actual changes in production management, and this results from insufficient yield verification practices. Several authors explain that it is not only agricultural producers, but the private insurance providers themselves that engage in such behaviors as they seek additional profits from government contracts (Wright and Hewitt, 1994; Barnet, 1999).

Weather-based Index Insurance

Miranda (1991) attributes the failures of the FCIP to many of these same problems outlined in the section above, and notes that the original programs of the 1940s experimented with area-yield based triggers for payouts. Area-yield insurance links payments to the average yield of a group of farmers spread over a distance, such as a county, largely removing the ability to profit from individual yield outcomes or inherently risk-prone farming practices. This is important because, as Miranda explains, any insurance plan that bases payoffs on metrics that are directly influenceable by policyholders will inevitably become inefficient. In response, he promotes the utility of the old area-based yield plans which were originally designed in response to this influence. Notably, before the term basis risk became popular, Miranda calculates that the value of an area-yield insurance product is directly related to the correlation of the areal yields to the individual policyholder's experienced yields. Area-yield plans were, as described earlier, eventually readopted by the FCIP, but the availability of more profitable yield- and revenue-based plans would limit their uptake.

Later, Barnett (1999) would promote the use of "put options" insurance plans, whereby payment would be dependent on some future condition as indicated by an index. These future conditions would be monitored by this index, often commodity prices, and payment would be triggered when its value fell below a certain level known as the "strike", and the amount of payment would depend on how far below the strike the value went. The term "basis" is used to refer to the difference between the index of conditions and experienced local conditions, most often broad market and local prices. Like many others at the time, Barnett also promoted the related practice of area-yield based insurance schemes as a way of dealing with the problems experienced in the FCIP's multi-peril plans.

The idea of a weather-based index is a clear extension of the put option and area-yield plans and represents an additional step away from behavioral influences. As described earlier, the independence of the index and decoupling of payout probability from management decision-making largely eliminates the possibility for advantage seeking, while the reduction of claims processing and yield verification significantly reduce operation costs and the premiums that farmers must pay (Zeuli and Skees, 2005). Perhaps most importantly, these insurance plans are geared towards loss from a singular cause. While the spatial extent of weather events will necessarily result in some correlated risk, the targeting of a single peril can be aimed directly at the costliest hazards for a particular practice and will invariably reduce the frequency and cost of indemnification.

Researchers do note some potential for adverse selection via weather forecasting that would have obvious implications for the success of rainfall-index insurance. As Nadolnyak and Vedenov (2013) would later examine in the case of weather-based index insurance and cyclical ENSO patterns, Luo et al (1994) found a source of potential adverse selection in the use of early seasonal rainfall and temperature forecasting. However, as Knight and Coble (1997) explain, this issue will become problematic only if the insurers neglect to incorporate the same weather information when setting yearly premiums. The potential weather forecast problem would more likely stem from institutional or budgetary constraints than from a genuine discrepancy in access to information.

Weather-based index insurance schemes, originally sold on the Chicago Stock Exchange and known as weather derivatives, first became available in the late 1990s as a way of accounting for losses in the energy sector following deregulation of the industry and were typically based on temperature (Vedenov and Barnett, 2004; Brockett et al, 2005). They quickly expanded into other sectors, but were used mainly for catastrophic loss and only began to gain popularity for crop-production purposes in the late 2000s. Today, much of the literature concerning weather-based insurance is related to the feasibility of its use for crop-production in subsistence economies where climate risk is high, affordability and access are major concerns, and where yield- or revenue-based insurance schemes are precluded by a lack of sufficient accounting and production data. In developed countries, crop yields are well documented and loss-based insurance programs are well established, but index insurance has still piqued plenty of interest as is evidenced by the creation of the PRF (Vedenov and Barnett, 2004).

Dealing with Basis Risk

A major trade-off for the benefits associated with rainfall-index insurance is basis risk; the quintessential concern of any weather index-based plan. This can be described as the risk involved with a contract written outside of the location being insured (Brockett et al., 2005; Woodard and Garcia, 2008), or as the risk involved with an uncertain correlation between the index and the value which is insured (Nadolnyak and Vedenov, 2013). These two descriptions are often distinguished as "geographic" and "production" basis risk, respectively, in order to identify sources of the discrepancy (Ritter et al, 2014). There is also a temporal form of risk, often discussed in terms of plant phenology, which is associated with inappropriate time-periods of coverage (Dalhaus and Finger, 2016).

The use of a precipitation index to accurately assess agricultural losses due to drought can be particularly troublesome due to the incomplete relationship between the meteorological drought it detects and the agricultural drought that results in experienced loss (Black et al, 2015). In the ranching case, different grasslands across the US respond very differently to a given amount of rainfall due to various ecological, geological, and climatic features (Heitschmidt et al, 2005; Moran et al, 2014; Knapp et al, 2015). While it would be impossible to argue that grasslands are not highly affected by precipitation, research finds that cumulative rainfall alone is a poor indicator of plant growth.

Muneepeerakul et al (2018) identify a source of production basis risk, showing that dryland crop yields in Kansas depend as much on the frequency and timing of rainfall (RIF) as they do on its accumulation. They hypothesize that small rain events might not be heavy enough to assimilate into the soil and large rainfall events might cause much of the water to runoff. To test for this, they develop an algorithm that infers drought stress, stomatal response, and evapotranspiration from soil moistures levels characterized by rainfall intensity as measured by: (1) the mean daily rainfall depth from days with at least some rainfall (mm), and (2) frequency as measured by the fraction of rain days to total days over the growing season. They validated their model on a two-year (2007-2008) rain-fed corn experiment in Belleville, KS. This experiment was chosen because total rainfall and average temperature throughout the growing seasons were similar while crop variety and treatments were held constant, which is a rare occurrence. Despite the similarities of the key variables, the two years had very different yields; 6.0 tons/ha in 2007 and 11.2 tons/ha in 2008. The rainfall patterns between the two years were very different (intensity = 15.0 mm, frequency = .22 per day in 2007; 22.3 mm, .15 per day in 2008). Their model used the rainfall data to predict yields of 6.81 tons/ha in 2007 and 10.7 tons/ha in 2008. They find that more intense but less frequent rainfall can lead to higher yields and make a compelling case for the inclusion of intensity and frequency measures in any rainfall-index insurance scheme.

Conradt et al (2015) identify temporal basis risk involved with rain-index insurance that is made available during fixed periods of the year. Because the growth period required for a particular crop is dependent on climatic factors and will vary among years, it is possible that these static period programs will frequently pay before or after critical times. To account for this they incorporate temperature and phenology of plant growth, in the form of Growing Degree Days (GDDs), into their own experimental index insurance design. GDDs are measurements of accumulated heat that determine how much time a plant will require to reach full growth. Different crops will only develop above certain temperatures, so there are different temperature thresholds set for each. Also, each crop will require a certain number of days above the threshold temperature to reach maturity. Accordingly, they use GDDs to determine start and end dates of an experimental cumulative rain index scheme used for wheat farms in northern Kazakhstan. This method minimized the chances of payouts due to rainfall deficits during non-important parts of the year for wheat, but could be used for any crop with known GDD statistics.

Ritter et al (2014) deal with geographic basis risk, which, as they describe, is dependent on two main variables. The first is the density of weather stations used to derive index values. In the case of weather derivatives that are based on singular data sources, geographic risk can be dramatically reduced by interpolation techniques, whereby the values from multiple nearby weather stations are used to estimate values in places with no observational data. However, the accuracy of such techniques depend heavily on the number of nearby weather stations available and, while there are techniques that compensate for this to a degree, there is only so much that can be accomplished without adding more stations. The second variable is the type of weather on which payouts are based. While a variable such as temperature is distributed along a relatively even and predictable gradient, precipitation varies significantly among even closely spaced stations, particularly in mountainous areas.

Common forms of interpolation are based on inverse-distance weights whereby the values from nearer locations influence the estimation of unknown values more heavily than farther ones. Ritter et al note that this method is insufficient for precipitation in particular, and so they design an alternative, geographically weighted model that bases the payoff itself on hypothetical payouts from contracts at nearby locations that do have weather stations (places with no geographic basis risk). The number of appropriate neighboring contracts to use in the weighting process is determined using simulated data and by iteratively adding neighbors until the error associated with the prediction is minimized. They find that, generally, the error values level off at around 5 neighbors. They note that they are operating in Germany where weather station density is high, so this number will depend on location. They were able to reduce payout errors due to geographic basis risk by about

20%, outperforming an inverse-distance index weighting method and another that simply uses historical payouts as weights when determining the current payout.

At least one assessment of basis risk involves the rainfall index used in the PRF. Maples et al (2016) look into the Rainfall Index Annual Forage Program (RIAFP), which is another RMA insurance product. This program was still in pilot mode at the time of this writing, and was only available in the central plains states for feed and fodder operations growing grasses, mixed forages, and small grains. The study examines correlations between the precipitation index and forage growth at three nearby locations in Oklahoma. It found that correlations between onsite rain measurements and the index are suitably high, indicating a lack of geographic basis, but it also found that correlations between plant growth and the index are particularly low and often negative, indicating high production risk. They conclude that the RMA index does not accurately reflect forage growth response in Oklahoma.

Another study assesses the basis risk involved with the use of a different index in an insurance setting, the Normalized Difference Vegetation Index (NDVI) (Turvey and McLaurin, 2012). The NDVI selects particular wavelengths from multispectral satellite imagery that are sensitive to differences in the prevalence and health of surface vegetation. This is particularly relevant to the PRF because, in an effort to better correlate the PRF index with rangeland forage, the RMA ran a pilot NDVI-based Vegetation Index program from 2007 to 2015 in selected counties concurrent with the rainfall-index pilot. It is particularly worthwhile to summarize because there could be no better method of reducing basis risk in the PRF than an accurate and direct measurement of rangeland productivity.

In the Turvey and McLaurin study, the utility of an experimental NDVI-based product was assessed for its ability to predict experienced loss using National Agricultural Statistical Service (NASS) hay, corn, soybean, and wheat growth data from 25 research stations across the US. This study generated a series of potential payouts triggered at a threshold of 0.5 standard deviations

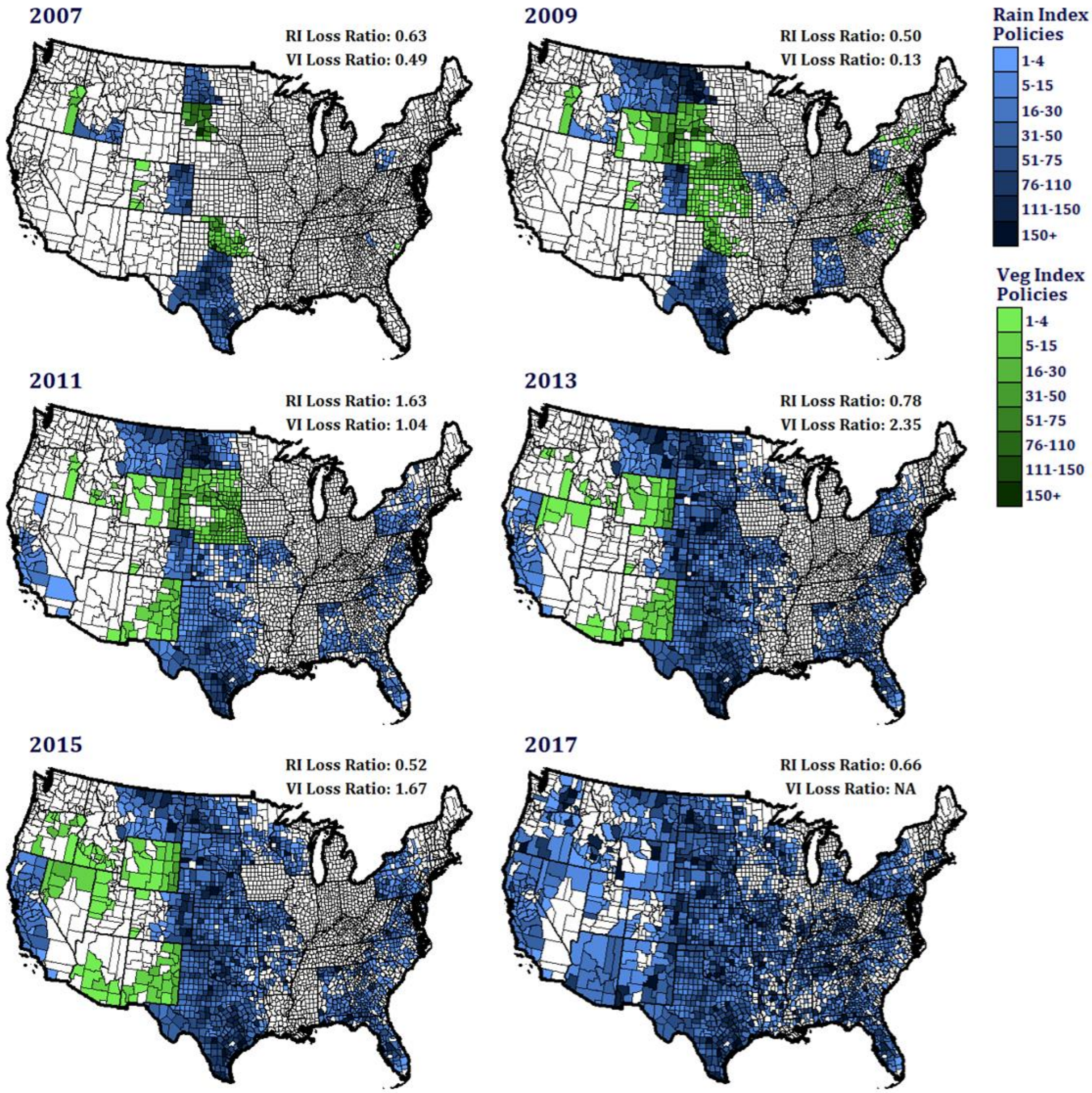

Figure 2. *Number of Pasture, Rangeland, and Forage Rainfall and Vegetation Index policies by county since 2007 with nation-wide loss ratios (total indemnity to unsubsidized premium ratios). The Vegetation Index option was dropped following the 2015 insurance year. Data source: https://www.rma.usda.gov/livestock (USDA-RMA, 2017c)*

below long-term NDVI average values for each location and compared payout frequency to observed loss frequency from the NASS statistics. It also included NDVI as an independent variable in regression analyses predicting yields for 23 of these locations. The results show that payouts are inconsistent with crop growth anomalies. The hypothetical payout frequencies for lowest-yielding quartile of years ranged from %0 in Heppner, OR to %71 in Rock Rapids, IA. The NDVI product would have paid %50 or less of the time for the majority of study sites during these low yield-years. The findings also showed that NDVI was an inconsistent and insignificant predictor in the regression analysis, often exhibiting inverse relationships with yield. The authors acknowledge the usefulness of an NDVI in certain applications and note that local-level calibrations might expand its utility, but generally advise against its use as a national-scale loss metric in an insurance setting.

A brief glance at the unsubsidized loss ratios associated with the vegetation index during the 9-year pilot phase of the PRF (Figure 2) shows a similar inconsistency and makes the reason for the decision to abandon the NDVI experiment clear. While the rainfall index maintains a relatively small and consistent fluctuation in loss ratios, ranging from 0.50 in 2009 to 1.63 in 2011, the vegetation index loss ratios vacillated erratically, ranging from just 0.03 in 2010 to 2.71 in 2012 (USDA-RMA, 2017c). While extreme events like the drought of 2012 might warrant periodic spikes in these loss ratios, the use of such an index would have led to a completely impractical actuarial situation for an FCIC program with a target ratio of roughly one.

CHAPTER II

DROUGHT INDEX DESCRIPTIONS

Drought indices were selected for their academic reputation at monitoring agricultural drought, their reputation and familiarity among broader groups, and, most importantly, because of the availability of historical records dating back to at least 1948. This last feature is required to properly compare their performance with the rainfall-derived index of the PRF which is based on average values since that year. The same drought indices are used in both the cattle market analysis in chapter 3 and the alternate index experiments in chapter 4, though some alterations were required for the latter analysis because of the unique structure of the PRF insurance program.

Evapotranspiration Estimation Methodology

A general description of the common methods of calculating evapotranspiration (ET) and potential evapotranspiration (PET) is in order to understand the drought indices that follow, as each of the temperature-based indices are capable of deriving PET via a variety of methods. The main distinction between the two is that ET is limited by the amount of water available in a system while PET represents the amount of water that could evaporate if sufficient water was present. The most common method used was developed by Charles W. Thornthwaite in the late 1940s to fill a conspicuous gap in the developing field of statistical climatology (Thornthwaite, 1948). Thornthwaite explains that the dryness of an area cannot be determined from precipitation alone, and that the measure must include some indication of its inverse: evaporation.

The actual evapotranspiration of an area depends on a complex interaction among physical, meteorological, and biological factors. However, in 1948 and for decades following, the accumulation of such information was impractical for most applications. Therefore, arguing that the bulk of potential ET can be described using temperature and precipitation, Thornthwaite traded specificity for practicality and developed a calculation based on these two easily measured variables along with the average length of day for each location based on latitude. The equation can be used to estimate experienced ET and PET for a location in terms of millimeters of water loss per month.

A more complex, and therefore difficult to calculate, equation was developed by Howard Penman (a contemporary of Thornthwaite) and John Monteith (Penman, 1948; Monteith, 1965). The Penman-Monteith method is seen as a more accurate method of performing the calculation, though, as Palmer (1965) would note, Penman himself was impressed by the performance of its simpler counterpart. The choice between the two in the development of a drought index is often a simple matter of utility. This method includes many different parameters that are derived from, or use directly, mean daily temperature, wind speed, vapor pressure, and latitude and is generally considered a more accurate and robust method.

Each of the drought index datasets used in this paper utilize the Thornthwaite method of calculation, though it would be possible to use other datasets with the Penman-Monteith or one of a variety of other more robust methods. For now, the availability of long temperature and precipitation records preclude the use of the more complete versions of ET and PET calculation, but in time it will be likely be possible to make the substitution and potentially improve the accuracy of each drought index.

Selected Indices

Palmer Drought Severity Index

The Palmer Drought Severity Index (PDSI) was an early attempt to describe the phenomenon of drought in numerical terms (Palmer, 1965). Created in 1965 by Wayne C. Palmer while working for the U.S. Weather Bureau, it has stood the test of time and, despite the development of many modern approaches at such quantification, the PDSI remains a widely-used indicator of drought conditions. It is based mainly on the amount of precipitation that an area must experience over a period of time to maintain locally normal soil moisture levels. A variety of indices are derived from the PDSI and three of those are included here. Because they are either extracted from or modified versions of this original method, a more detailed description of the PDSI is presented to make their utility and distinctions clear.

Temperature, precipitation, and soil moisture capacity variables are required as inputs for calculating the PDSI. Soil moisture is divided into two "arbitrary" depths, a one-inch surface that receives rain and from which water first evaporates, and the underlying root-zone from which plants extract moisture. Soil moisture loss (L) is considered the key indicator of drought impacts and is calculated as a function of precipitation, potential evaporation, runoff, and the ratio of available surface soil moisture to the combined water holding capacity of both soil levels. The amount of precipitation needed to maintain normal soil moisture levels ($\hat{P}$) is calculated using values deemed "Climatically Appropriate for Existing Conditions" (CAFECs). These coefficients are ratios between average and potential ET ($\overline{ET}/\overline{PET}$), runoff ($\overline{RO}/\overline{PRO}$), recharge ($\overline{R}/\overline{PR}$), and soil moisture loss ($\overline{L}/\overline{PL}$) specific to each location. Each of these ratios are then multiplied by observed potential values for the time and location of the index value calculation. The first three terms are added together and the last subtracted to determine $\hat{P}$. The difference between observed monthly precipitation (P) and this level of precipitation is then used to calculate the moisture departure (d).

$$\hat{P} = PET\left(\frac{\overline{ET}}{\overline{PET}}\right) + PRO\left(\frac{\overline{RO}}{\overline{PRO}}\right) + PR\left(\frac{\overline{R}}{\overline{PR}}\right) - PL\left(\frac{\overline{L}}{\overline{PL}}\right)$$

$$d = P - \hat{P}$$

Average moisture departure ($\overline{D}$) for each month is then inserted into another algorithm that is designed to calculate a local climatic characteristic (K) to account for spatial variation in moisture departure patterns:

$$K' = 1.5 \log_{10} \left(\frac{\frac{\overline{PET} + \overline{R} + \overline{RO}}{\overline{P} - \overline{L}} + 2.8}{\overline{D}} \right) + 0.5$$

$$K = \frac{17.57}{\sum_{m=1}^{n=12} \overline{D}_m K'} K'$$

The observed moisture departure (d) is then multiplied by this local characteristic (K) and becomes what is called the Z Index (dK), an independent drought index that incorporates only the conditions observed for that month. The PDSI itself is autoregressive in nature, it depends on prior PDSI values in addition to the current Z Index value. To calculate the current PDSI a constant of .897 is used as the weight of the prior month's PDSI influence, and 1/3 is used as the weight of the current Z Index. These are called duration factors. The PDSI then becomes:

$$PDSI_t = .897(PDSI_{t-1}) + 1/3(Z\ Index_t)$$

Notably, the issue of "man-made" drought was considered and avoided in the development of this algorithm and Palmer only used input variables that are independent of water management practices such as irrigation (Palmer, 1965, pg. 3). Because this process is centered around soil moisture, it is an appropriate index for detecting agricultural drought.

Self-Calibrated Palmer Drought Severity Index

Computational constraints and data availability necessarily restricted the local specificity that Palmer was able to incorporate into his index. The constants used to determine the duration factors were derived using empirical data from only western Kansas and central Iowa. The data for

Kansas represented an area containing 31 counties between 1887 and 1965, while those for Iowa were collected between 1931 and 1957 representing only 12 counties, which means that the autoregressive portion of the calculation is largely reflective of patterns in western Kansas.

Constants used to calculate the climate characteristics of each location were derived using data from Iowa, Kansas, North Dakota, Ohio, Pennsylvania, Tennessee, and Texas, and are, therefore, more representative of the US as a whole, though they neglect the far West. To help compensate for this, and allow for improved comparability between locations, Wells et al. 2004 developed the Self-Calibrating PDSI with a method that sets the duration factors and climate characteristics using local baseline climate conditions and observations of the PDSI itself.

Palmer Z Index

The Z Index is part of the PSDI calculation and represents the single monthly precipitation departure from that required for normal soil moisture, regardless of prior conditions. It thus can also stand alone as an indicator, often referred to as the Soil Anomaly Index.

Several studies have found that the Z Index is well suited for monitoring agricultural drought because of its ability to account for shorter term changes in soil moisture. Karl (1986), in assessing the sensitivity of the PDSI to the calibration period, was one of the first to surmise this quality of the Z Index. He also showed that Z was much less sensitive than the PDSI to the calibration period used as the indexing baseline, which could be another useful feature for an index in an insurance setting. Quiring and Papakryiakou (2003), using a Palmer Z Index with a slight adjustment to reflect Canadian Prairies, compared its model fits with Canadian wheat production, as a dryland crop reference for grassland, to those of the PDSI, SPI, and another index called the NOAA Drought Index (NDI). The Z Index had significantly higher R^2 and Index of Agreement values, as well as significantly lower root-mean-squared errors and mean-absolute errors. Vicente-Serrano et al (2012) found that the Z Index outperformed three other varieties of Palmer drought indices in an analysis of world-wide wheat production.

Standardized Precipitation Index

In 1993 Thomas McKee, Nolan Doesken, and John Kleist of Colorado State University first incorporated what is now a common element in new drought indices: multi-scalar drought calculation capability (McKee et al, 1993). Because the impacts of a drought are felt at different time scales by different stakeholders, this feature is important to more fully describe them. Whereas a water supply manager might be concerned about drought over a period of a year or more, a corn farmer might be more concerned with SPI conditions over the four- or five-month growing season.

Simple standardized precipitation can be calculated as the difference between observed and average precipitation for a location and month divided by the standard deviation of precipitation for that location and month. Standardization is typically based on average values, the SPI uses gamma-distributed probabilities of rainfall amounts derived from historical data over a moving average at various monthly-time intervals, with the intervals chosen depending on the use case. The gamma distribution shape can be seen in the distribution of the rainfall index used in the PRF. This results because of a necessary cutoff of values at 0mm and a long range of decreasingly frequent large rainfall events. The probabilities of observed precipitation values are determined based on this distribution and used to calculate probabilistic deviations from the baseline. The result is a normalized probability distribution, centered around zero and with a standard deviation of one, and negative values representing precipitation deficiencies.

The SPI might not use evapotranspiration to incorporate temperature effects, which is an important factor in describing drought, however, regarding moral hazard, Muneepeerakul et al made a compelling observation: any potential agricultural insurance index that uses evapotranspiration is vulnerable to alteration by the policyholder because that variable is partly dependent on plant production. While this observation was made in regard to crop production, and the other indices studied here use potential evapotranspiration with no input of vegetation information, it presents a possible challenge for any potential index-insurance scheme that does. Also, as will be described in chapter 4, problems could arise with the calculation of evapotranspiration in future as the climate warms. Therefore, the SPI is included in this study of alternative drought measures for insurance applications in case this concern arises in future agricultural insurance schemes. Because of its simplicity and the expanded utility afforded by the multi-scalar feature it may provide an easy means of reducing basis risk for a rainfall-index product.

Standardized Precipitation-Evapotranspiration Index

The Standardized Precipitation-Evapotranspiration Index (SPEI) builds on the SPI by incorporating PET (Vicente-Serrano et al, 2010). Where the SPI uses monthly precipitation, the SPEI uses the difference between monthly precipitation and PET, and where the SPI fits historical trends to a probabilistic gamma-distribution the SPEI uses a log-logistic distribution. The developers of the SPEI chose the Thornthwaite method because, in addition to the reasons described above, the application of PET in a drought index setting does not necessarily require the most precise algorithm available since the value is used as a relative measure, relating observed conditions to baseline averages. They cite Mavromatis (2007), who measured the PDSI's ability to capture wheat production variation with both the Thornthwaite and the more complex Priestley-Taylor methods for PET, finding little difference in index performance between them. Importantly, they cite many studies that point to the importance of temperature in determining drought impacts. One study finds that the PDSI responds roughly equally to deficits in precipitation as it does to corollary increases in temperature (Hu and Willson, 2000).

Vicente-Serrano et al. (2012) performed a unique global and multi-system assessment of the SPI, SPEI, and four different versions of the self-calibrated PDSI. They calculated Pearson correlation coefficients between drought index values and time-series data of stream-flow, soil-moisture, tree-ring thickness, and wheat yields from around the world. Taking advantage of the multi-scalar properties of the SPI and SPEI, they ran the correlation with 1- to 48-month versions of each, and kept the results with the highest correlations. This is a good example of the exploratory analysis that can be employed to discover the best indicators of drought using multi-scalar indices. They found that both the SPI and the SPEI usually outperform the PDSIs. In the assessments of their ability to predict global soil moisture and wheat production, which relate more closely to forage production than the others, the SPEI outperformed the SPI. Noting examples where the Palmers outperform the SPEI, the authors tentatively suggest, in the absence of foreknowledge of a system's sensitivity and where similar assessments of index performance are not possible, that the SPEI is chosen.

Data

Each of these drought indices were acquired through the West Wide Drought Tracker (WWDT) of the Desert Research Institute in Reno, NV (Abatzoglou et al 2017). This portal was created to help fill the need of stakeholders for easily obtainable drought monitoring products with long historical records and fine spatial resolutions. The WWDT provides drought index datasets that were developed through the University of Oregon's Parameter-Elevation Regression on Independent Slopes Model (PRISM), which was designed to account for orographic disturbance in climate data collection using a digital elevation model in tandem with other supporting spatial data. The original datasets included drought indices were retroactively calculated back to 1895 using temperature and precipitation data at a spatial resolution of 1/24th decimal degrees. Datasets from 1948 to the end of 2016 were retained and resampled to 1/4th decimal degree resolution to match that of the RMA index.

CHAPTER III

CATTLE MARKET ANALYSIS

Quantifying the relationship between a weather index and economic impacts in the livestock grazing industry is not straightforward. In crop production the commodity itself is insured, and is well documented and quantified. In the PRF the grassland and feed crop forage upon which the industry depends is insured, but these are only inputs of the marketed commodity. There is no corollary metric currently available that could serve as a "ground truth" for determining loss and establishing index correlations.

The use of a Normalized Difference Vegetation Index (NDVI) seems like a straightforward way to capture a baseline for drought induced forage-damage, but there are variety of reasons related to scale to avoid its use in this application. An NDVI will pick up a relatively coarse resolution of all plant production in an area, including plants with various drought resiliencies, and may not be sensitive enough to detect critical levels of grassland damage at smaller scales (Rowley, 2007).The NDVI is differentially sensitive to temperature and other geographic features of local landscapes, particularly in the Great Plains, which means that NDVI values in one area of the United States may not be comparable to those in other areas (Tan, 2007). Research shows that an NDVI value is more accurate at capturing vegetation impacts over long time-scales. Work in the plains of Kansas found that the highest correlations between NDVI and precipitation values occurred when the data was aggregated over a 15-month period (Wang et al, 2003), while the insurance intervals used in the PRF span only two months. Also, as described in chapter one, this product was used experimentally as the index itself in the PRF pilot program and failed due to large vacillations in loss ratios, which on its own is reason enough to avoid it as a loss metric when determining the basis risk involved with the PRF. There are several local-scale studies that correlate agricultural productivity with drought index values, but while those are certainly valuable, they do not provide a complete enough picture for a national-scale assessment of indicated grassland health (Moorehead et al, 2015, Knutson et al 2016).

In the cattle production industry, as with any other, loss can be described in terms of changes in revenue. While water deficits that lead to lost forage productivity and subsequent carrying capacity of a range can be classified as agricultural drought, the impacts experienced by ranching businessmen are most pointedly felt in altered prices, added feed costs, and lower weights from premature cattle sales. This indicates the presence of what is referred to as a socio-economic drought (Wilhite et al. 2014). Indeed it is this socio-economic drought that is insured against; the program is specifically designed to help allay additional costs of supplementary feed when grassland productivity drops during drought in order to provide sufficient funds for economic recovery. Therefore, in lieu of real-time, nation-wide forage productivity monitoring, it is appropriate to search for the impacts of such loss in economic data. I argue that an appropriate assessment of the ability of an index to indicate drought-induced loss in the cattle production industry might be made using cattle market data, which is more readily available for large portions of the United States and directly related to the impacts that an efficient insurance program must protect against. In this chapter, using a large dataset of live cattle auction information from the USDA's Agricultural Marketing Service, I assess the ability of various drought indices to predict cattle weights, which is a variable that both depends on forage and feed crop productivity, and is a major determinant of revenues; thusly situated in between the agricultural drought that causes vegetative productivity losses and the socio-economic drought experienced by ranching businessmen.

Related Research

There are several studies that seek to find and quantify a climate signal in market data. These vary in complexity depending on the goal of the analysis, the market good in question, and the climate variable used. Because the effects of weather and climate on a commodity are rarely simple, each study must give significant thought to the theoretical relationship between the two, or exploit some feature of the commodity that best isolates the climate effect.

Holopainen et al (2012) search a hundred-year record of crop yields and prices for an effect of temperature in 19th century Sweden as the Little Ice Age waned. This study was performed to help understand the agricultural impacts a warming climate might cause in the area. A time series of temperature starting in 1802 was generated from measurements taken at Stockholm and Uppsala in the south of Sweden, and in Tornedalen, Finland near the northern Swedish border. These data were averaged into a country-wide metric and associated with fluctuations in both a nation-wide crop production index generated with data from the Swedish Central Bureau of Statistics that began in 1786 and individual records of rye, barley, oat, and wheat yields that were available starting in 1860. Temperature was also associated with commodity prices using data from a different study that collected 183-year record between 1732 and 1914 (Jörberg, 1972 a & b). After correcting for trends in yield and price variability with a cubic smoothing spline they performed Pearson correlations of both the crop yield index and price data with detrended average temperatures of the 14 months prior to harvest for the period between 1803 and 1914. The same was done for the individual grain yields between 1860 and 1914. The winter months were included because of fall-planted grain varieties. The Pearson correlations were then complimented with principle component analysis (PCA) regressions. A second set of analyses that separated the cold and warm season influences were also performed, with the cold season corresponding to the months between August and February and the warm season corresponding with March through September of the year prior to harvest.

As might be expected, both correlation and PCA coefficients between all yield metrics and temperature were strongly positive, while those between price and temperature were negative. The influence of temperature on yields was considered to be more important than that on price as the latter had a consistently weaker relationship. This effect remained when the warm and cold seasons were isolated, indicating that warming in the region would be, overall, beneficial to crop production. This effect was corroborated by previous research in neighboring Finland (Holopainen and Helama, 2009). It was also found that price correlations between individual grains were much greater than yield correlations between individual grains and this was taken as evidence that, given the risk of starvation throughout the Little Ice Age, the Swedish people made efforts to reduce the volatility of price and sensitivity of the market to any single crop failure.

In an analysis of the wine market, Ashenfelter (2008) takes advantage of the constancy of Bordeaux wine production methodology to isolate the effects of weather on price and quality. The wine making process in the Bordeaux region of France has not changed much in centuries, though prices fluctuate drastically from year to year. For example, the average London Auction price across all major Bordeaux region vineyards for a bottle of wine produced in 1961 was $407 by 1990 while the average price from the same vineyards from the very next year was only about $82. Quality serves as the main determinant of price which can, therefore, serve as a suitable indicator. The author notes that the ultimate quality of a bottle of wine has, historically, been largely a mystery until it is opened. In this study, the author sheds some light on the mystery using temperature and precipitation data during the growing seasons of five major vineyards in the Bordeaux region between 1954 and 2003.

Ashenfelter runs OLS regressions on the log price of wine with and without weather variables. The first model includes only the age of the wine, which alone explains 21% of price variation. The second model predicts price using the age of the wine along with average temperature in the growing season from April to September, precipitation in August, and precipitation from October to March, which are all critical periods for vineyards in this region. This model explains 83% of the price variation in the Bordeaux region, validating the presence of a strong weather signal in the prices of wine. The analysis indicates that the highest quality vintages come from years with warmer than usual temperatures and lower than average precipitation in the growing season. All but one of the highest priced vintages were produced in years with warmer than normal temperatures in the critical summer months, and the superior 1961 vintage mentioned earlier came from a record setting dry late summer to fall period. Using this model he was able to counter the expectation of professionals and predict high quality wines from the years 1989, 1990, 2000, and 2003; years which have subsequently been accepted as "outstanding".

In an econometric analysis of the stock market, Hirshleifer et al (2003) find a strong relationship between daily cloud cover and local market index returns. The authors use weather data from 1982 to 1997 for 26 international cities acquired through the International Surface Weather Observations (ISWO) dataset of the National Climatic Data Center (NCDC-NOAA) to derive daily snow, rain, and cloudiness (in the form of total sky cover) measurements. Daily index return data were acquired either through an index called the Datastream Global Index or local indices for locations with shorter Datastream histories. They then apply increasingly complex econometric methods to test the hypothesis that sunshine affects moods which in turn affects a general willingness to trade and thus the frequency of returns.

The first method was to use univariate regressions of daily nominal returns on the nation's stock index as a function of cloudiness for each city. Cloudiness deviations from normal conditions for each time period and place were used in place of the original data to avoid seasonality. 18 to 25 cities, depending on model specification, displayed return patterns that had a negative relationship with cloudiness. They then performed joint parametric tests with the entire dataset. This was a pooled regression, holding intercept and independent variable coefficient values constant for each location, and it showed a highly significant relationship between cloudiness and returns. However, this test assumed independence of the error term from predictors and so would not result in unbiased coefficients.

To account for this problem they estimate a fixed-effects model with panel corrected standard errors (PCSEs). This method allows the errors to be contemporaneously correlated with predictors, autocorrelated with each other across time for each location, and to be heteroskedastic between locations. The effect of such a correction is to provide more accurate standard error estimations, but also to increase their general magnitude. However, despite these additional constraints, they again find a highly significant relationship. Then, to distinguish between the effects of other weather variables such as rain and snow on stock returns, they add these variables to the structure above in a multiple regression finding little significance of effect from these variables; it appears to be a simple lack of sunshine that drives the response. The effect of sunshine on stock returns is large; for example, in New York City the market return on completely sunny days is 24.8% per year while the returns during completely cloudy days average 8.7% per year. New York is the most volatile of all study cities in terms of trading sensitivity to sunlight, but the effect is very distinct for markets across the world.

These findings represent a rather circuitous example of the relationship between weather and markets. The authors attribute the effect of sunshine on stock returns to psychology; namely the misattribution of stock market outlooks to one's mood. There is extensive literature on the phenomenon, and it fits with the expectation that sunshine engenders positive moods and positive moods increases the perception of the chances of success. Translating into stock returns, this tendency increases the willingness to trade which increases trades and returns.

Few papers exist that deal with climate effects in the US cattle production market, but at least one relevant paper examines exactly that. In a singular event study, McFerrin and Wills (2013) used market data on shipping trends via the Chicago Union Stock Yard from 1881 to 1903 to search for signals of the infamous "Great Die-Up" during the winter of 1887, which followed a severe drought and led to reports of wide-spread cattle death. The authors isolated data on Texan, Indian, and Northwestern range cattle, three common breeds of the era that moved from western ranges through the stock yard at high volumes. They conducted a time-series analysis using autoregressive and seasonal moving average regressors to detect significant structural disruptions in cattle shipment trends according to Wald Chi-squared statistics.

In a rebuff to the common narrative of widespread cattle die-offs and excessive stocking of the commons, 1887 did not show any significant structural disruptions in shipping. Prices for Northwestern cattle did jump significantly by 1888, as would be expected given a dearth of supply, though this was not accompanied by any corollary fall in recorded Northwestern shipments. The event, according to the market data, was simply not as severe as purported. Citing several academics and the Daily Drover's Journal (which was founded specifically to report on the Chicago Stock Yard), the authors note that there were many examples of exaggeration in the news reporting of the day. While the occurrence of the event is not denied, it is explained that western cattlemen, in an age of tenuous land tenure, likely saw the event as an opportunity to discourage new comers from entering the market by spreading misinformation. Considering the data they make a compelling case.

The event-study did find a very extreme event in 1899, and a relatively extreme one in 1892. They found that these disturbances corresponded well with significant financial shocks of the time, such as the McKinley Tariff Act that raised import fees by as much as 50%. The relative sizes of western population had necessitated heavy dependence on eastern and foreign capital. Cattle commission companies had been formed to provide the capital needed as the industry expanded and investment had been growing dramatically since 1880. By the time these shocks occurred the cattle industry had become intertwined with global financial markets and sensitive to distant events.

This research takes advantage of the era; the Chicago Stock Yard was highly representative of the market as a whole and so a single-location time-series analysis could be justifiably employed. Today, there is no singular location that could be said to represent the cattle industry as such and so the effect must be sought on a local level. It might also be worth mentioning that they did not actually find a climate signal, they instead found one of national policy in a context of increasing international sensitivity. While it is certainly possible that the accounts of livestock losses in 1887 were exaggerated, it is highly unlikely that the drought event was completely fabricated, and, assuming it was not, even more unlikely that it did not have some effect on the cattle market. This would suggest that, in order to discover evidence of a locally-specific phenomenon such as drought in market data, it is necessary to use local- or regional-scale indicators.

Analytical Methods: Fixed-Effects Panel Modeling

To compare the ability of each drought index and the precipitation index to correlate with the economic effects of drought, an econometric panel data method is employed. The panel format, also referred to as "longitudinal data", is a combination of cross-sectional and time series formats. By allowing the modeler to leverage variation in the variables of interest both between individual entities and across time, panel data provides added flexibility and statistical power over either of these two formats alone. This added dimension of variance results in datasets with less collinearity between predictor variables as differences between locations are less likely to co-vary. Panel datasets also tend to contain more observations which generates more degrees of freedom and results in generally more efficient estimations. Most importantly, by allowing the modeler to group by location or time it enables them to account for unobserved heterogeneity between sites, or time periods, that would cause bias in a pooled data ordinary least squares (OLS) regression (Baltagi, 2008).

Basic OLS estimation typically cannot not be applied to panel datasets; there is an increased likelihood, and almost certainty for observational data such as ours, of correlated errors due to cross-sectional dependence. For example, rainfall on a ranch in Colorado may have sufficient variation between time periods to use as an explanatory variable of forage production in Colorado, and might do so without violating the OLS assumption of zero correlation between regressors or dependent variables and the error term. Rainfall would vary consistently above or below the mean unless there is some unobserved temporal trend. However, when these observations are pooled with those from a ranch in Florida, where rainfall patterns are completely different and swing much farther above and below its average, the errors will become dependent on location. If location is not incorporated appropriately into the model the errors will not vary consistently across observations and will necessarily correlate with both the dependent and independent variables. If location is included in the model using panel methods, any correlation can be attributed to site-specific attributes and dealt with.

The basic form of a panel model equation used in this analysis is similar to that of an OLS, but there are a few added terms to account for the indexed time periods and individual groups. The individual index can refer to a singular entity of any type, and the time dimension can actually be substituted by any second dimension, but it is time and location that are of concern in this analysis and so those terms will be used to describe the process here. The equation is formulated as follows,

$$Y_{it} = \beta X_{it} + \boldsymbol{\epsilon}_{it}$$

while,

$$\boldsymbol{\epsilon}_{it} = u_i + v_{it} \,,$$

where Y_{it} is the dependent variable at location i and time period t, β is the effect of a vector of independent variables, X_{it}, at location i and time t, and the error term $\boldsymbol{\epsilon}_{it}$ is the combination of an unobserved, location-specific intercept u_i and an idiosyncratic error term v_{it}, which is unique to each time step and location and is assumed to be independent with constant variance. With this there are several ways to estimate model effects, either by using least-squares dummy variables (LSDV) in an OLS, by modifying the data to remove these effects and then running the OLS, or by using more complex estimation methods with non-linear estimation strategies such as Generalized Least Squares (GLS). The simplest estimation strategy is called the "between" estimator, where the data values associated with each term in the equation are averaged over time for each location and then used in the OLS as if the data were a basic cross-section. This will account for cross-sectional error correlation, but removes any temporal variation and reduces the explanatory power of the model. After that is the LSDV strategies, whereby a dummy variable is added for each location or time period to account for fixed effects along these dimensions. With smaller panels this is a feasible strategy, but with panels that have a large number of locations or time-periods the number of dummy variables required can become unmanageable and difficult to interpret. In this case the coefficients of the independent variables will be accurate, but those on the location specific-effects can easily become inconsistent. Another method is called the "within" estimator which is slightly more complex, but similar to the "between" strategy. This method subtracts location-specific mean values from each observation for every time period before performing an OLS. This maintains time-varying information and is often sufficient to remove cross-sectional dependence, though it does remove any site-specific constant information. When this model is estimated the resulting coefficients and model fits must be interpreted from the reduced dataset that results from the transformation, and this is known as the demeaned model. The resulting diagnostic values are from a model that has effectively had its intercept term removed, because of the fixed-effect subtraction, and while coefficients on both independent variables and the fixed-effects will be consistent, the model fits will be misleading. One way of extracting model fits is to report the R^2 of the LSDV model while maintaining the coefficients and standard errors of the within estimation (Hun, 2011). Another technique is referred to as random effects.

A random effects model uses non-linear estimation such as GLS to maintain much of the information that is lost to a fixed-effects model, is considered more robust and complete, and is preferred where possible. In contrast, with a fixed-effects strategy, if there are any site specific constant variables, such as an ecoregion or grassland type, this information is removed. The same principle applies if the data has fixed time-effects that would apply to all locations, such as a nation-wide price depressions or other market-disturbances. While random effects models are able to maintain this information, they are consistent only when there is no correlation between regressors and the unobserved site-specific intercept term in the panel model equation. When this condition is met both the fixed- and random-effects models will be consistent, but the random-effects model will be more efficient with smaller standard errors. Where this condition is not met, the fixed-effects model must be used to produce unbiased estimates; by removing site-specific effects it ameliorates the correlation issue. The presence of correlation, and therefore the best choice between fixed- and random-effects models, can be detected using Hausman specification test (Hausman, 1978). This diagnostic tests against the null hypothesis that there is no endogeneity in the model. Models for each of the various drought indices rejected this null hypothesis and so the fixed-effects method was used for each.

Even though a fixed-effects model will account for cross-sectional sources of correlated errors, there may still be heteroskedasticity or correlation between regressors and the error terms within each group. If this issue is not attended to, artificially low standard errors and p-values will be generated which can lead to misinterpretation of the effects on the independent variables. When the number of groups is large, the error variance-covariance matrix of the model can be restructured following the specification of a fixed-effects model to reflect more realistic standard errors using standard error estimation techniques that group by location (Cameron and Miller, 2013). The technique used in this study is referred as the robust estimate of variance. It was specifically designed to create standard errors that account for heteroskedasticity and serial correlation and is commonly used in fixed effects panel models (Huber, 1967; White, 1980). By allowing errors to be autocorrelated within each location, as would be expected for samples responding to the same local conditions, the robust estimator is used to calculate panel model effects in a way that maintains independence between locations by sacrificing some model significance and increasing error values, thus enabling a much wider range of model specifications to fulfill the Gauss-Markov assumptions.

Methods

Establishing the Theoretical Relationship

The effect of drought on market activity results from a dynamic process that involves the state of the market as a whole, physical responses of cattle and grasslands to local climate, and the decision responses of ranch managers trying to minimize lost revenue (Countryman, 2016). A climate effect should exist for each aspect of this process because cattle and feed prices will respond to weather conditions on a larger-scale, while at the local-scale managers will themselves respond to either experienced or expected physical responses of the land to climate (Crimmins and McClaran, 2015).

To capture the effect of local drought it is important to consider deficits over the critical growing months during both the year of sale and the year prior, which may still show ecological effects of damage if the deficit was great enough (Griffin-Nolan et al, 2018). After examining the various potential market variables as possible indicators of drought, it was determined that the strongest and most independent climate signal would likely exist in the fluctuation of cattle weights. Drought will motivate ranchers, a significant portion of which run cow-calf operations, to sell their stock early at lower weights, sacrificing the profit that could be gained from longer grazing periods to avoid expensive supplementary feed costs and damage to the drought-stressed range. Cow-calf operations are particularly impacted because breeding mother cows make up a portion of this stock and prices for "feeder" calves, or calves that are intended for continued grazing, are the first to fall during drought (Countryman, 2016). If the market report records kept track of the age of the animals being sold the data would have been filtered for calves and yearlings because they make up the most fungible resource of a cow/calf producer's stock and this group's weights are expected to be the most sensitive to climate variation. However, the only possible indicators of age in the records are numerical variables describing weight ranges and categorical variables describing frame size, the latter of which is likely recorded in relation to the former. Because the weight ranges are already used to determine the dependent variable it would be problematic to use them to infer age. Despite this restriction, the climate signal ought to apply to all age classes at market to some degree. At worst the effect would be neutral; if a rancher is going to sell a steer, that steer will certainly not be any heavier if there has been drought. Therefore, the various classes, frame sizes, and weight ranges of the cattle have been pooled.

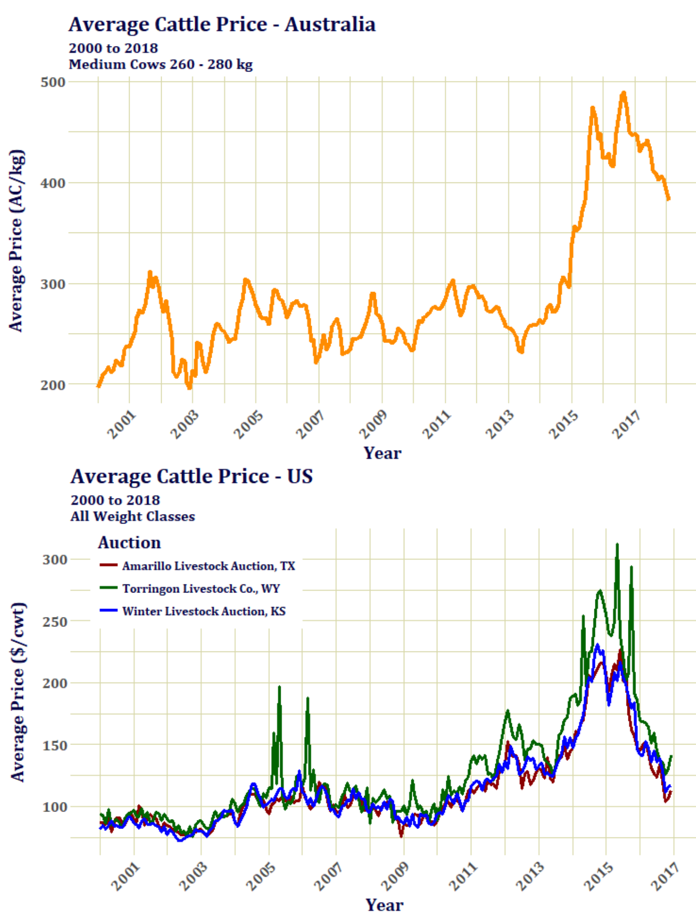

Figure 3. *Average prices from three US auctions at different latitudes and medium cattle weight class prices in Australia indicate the presence of broad national and international trends.*

Any market variable in our dataset that is involved with price is heavily dependent on national and international market trends, and will fluctuate according to a very distinct pattern regardless of location. It would be possible to detrend price by taking the differences between consecutive time steps and searching for a climate signal in the resulting variation because price would be expected to fall during drought when the market experiences higher sale volumes. However, because the purpose of this analysis is to use market data to find the index that best reflects revenue loss from low forage production, and cattle weight is directly related to both rangeland health and producer revenues, weight was chosen as a more appropriate source of a climate signal. Price was, however, expected to influence cattle weights independently of climate fluctuation by influencing the decision-making of the producer. A high price may very well prompt early sales regardless of drought so it is included as a predicting variable.

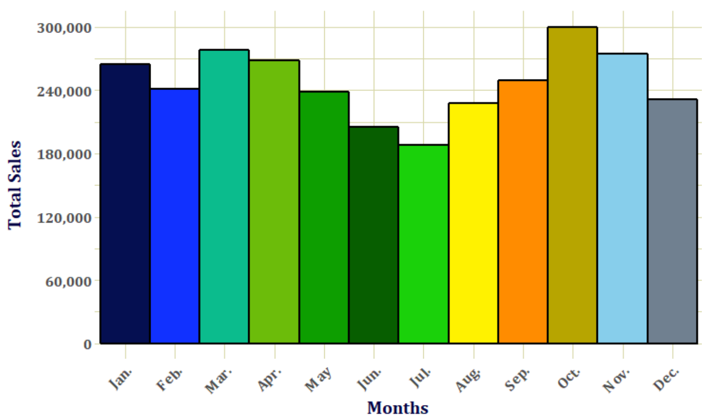

Figure 4. *Monthly sale from the US cattle auction dataset between 2000 and 2016. Auctions have the most sales in October and March and the least in July and June. Data source: USDA Agricultural Marketing Service.*

There are two main sale seasons according to the data. These occur in the early spring and late fall, though this varies from place to place. There are somewhat more sales during the fall season after the end of the growing season after the animals have reached their maximum weight before requiring supplemental feed. The overall dataset exhibits little seasonality in average cattle weights, though the fall season does indicate somewhat lighter weights. When the data is isolated by auction, however, there are distinct seasonal patterns that emerge which depend on the location. Generally, the farther north the auction is the more seasonality in there is, with heavier weights showing in the summer, while the most southern markets maintain a steady average weight throughout the year. To account for this seasonality and improve model performance in these northern sites, a one year lagged dependent variable is included as a predictor. This is intended to account for any additional effect of the month of the year that remains after the fixed location and time effects are applied to the model estimation.

The link between climate and market is not direct; there are several degrees of separation between them. Dry conditions during the month of sale are not likely to cause widespread early sales, though this time period is included because it may be an indicator of a trend that lead to the decision, especially for the risk averse producer with an eye towards forecasted information. Depending on the risk tolerance of the producer, market effects might require visible rangeland deterioration before sale plans are altered, or sometimes the animals might begin to show signs themselves. Independent of the decision to sell, forage will not deteriorate significantly from a single dry month; it will take an accumulation of poor conditions over time. There will be significant temporal lagged effects of climate, with the expectation that conditions during the most recent growing season will be most important at determining forage production and subsequent weights during sale time. Also, significant droughts during one year's growing season may still impact forage production in the next. Because of the large north-south extent of the study area, there is no singular set of months that can be associated with a study-wide growing season, and southern auctions will often represent the practice of year-round grazing. Therefore, to capture the full effects of drought, index values from the entire previous two years are included in the model. To avoid excessive collinearity, monthly index values were aggregated into seasonal means for the two years prior to sale so that the model formula becomes:

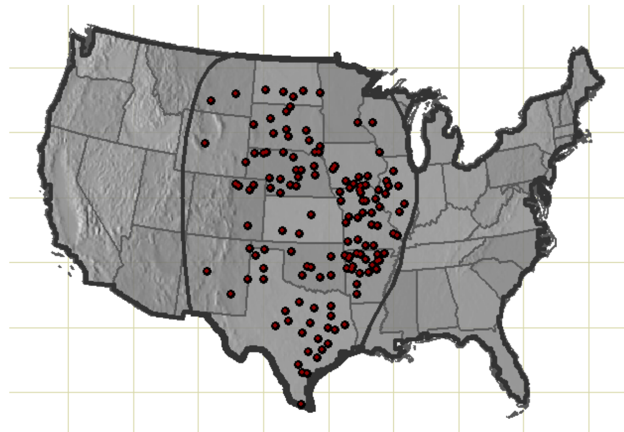

Figure 5. *The 144 Central U.S. live-cattle auction market locations used in this studv.*

$$\boldsymbol{Log\,Weight_{it} \sim Log\,Weight_{i,t-12} + Price_{i,t} + Winter_{i,t1} + Spring_{i,t1} + Summer_{i,t1} + Fall_{i,t1} + Winter_{i,t2} + Spring_{i,t2} + Summer_{i,t2} + Fall_{i,t2},}$$

where the seasonal variables are average drought index values for the first and second year preceding each sale, price is an arithmetic monthly mean in dollars per hundred weight, and the one-year lagged dependent variable is added to account for seasonal trends in weight.

Data Collection

Cattle market sale data was acquired through the USDA's Agricultural Marketing Service's publicly available custom report tool (USDA-AMS, 2017) and is comprised of 5,675,600 live auction sale records from January 2000 to December 2016. Records are collected as parts of weekly summaries of sales at each auction and include a cattle class description, a muscle grade description, head counts, weight ranges, average weights, price ranges, and average prices. The dataset contains, overall, 291 live-cattle auction locations, though the number of reporting auctions vary from month to month. Reporting for auctions mostly depends on agreements between state and federal marketing agencies, the availability of state and federal reporting agents, and the number of sales an auction experiences in a month. For each month there need to be enough sales to warrant a report because low sale numbers can lead to artificially inflated prices that are not reflective of the market. This number depends on the state. For example, Missouri will not report any monthly auction activity with fewer than 500 animals sold, while marketing agents in other states will stop reporting under 1,000. This occurs to some degree on a seasonal basis between the late fall and winter sale runs, and to a larger degree during the spring before calf weaning. A permanent cessation of reporting at a particular sale barn might result from consistently light receipts, or if an auction barn owner decides not to allow further reporting. Reporting is voluntary; owners can decide whether or not to allow state or federal reporting, though, if they do agree, they cannot decide when reporting can and cannot occur (Pitcock, 2017). This reflects a principle of the AMS to accurately indicate market activity and maintain consistency.

The auction sites are concentrated mostly in the central and southeastern states. Locations west of the Front Range of the Rocky Mountains and in the Northeast are sparse because of a lack state-federal marketing agreements. While it may have been possible obtain cattle auction data through individual state marketing services, the information collection methodology involved is very unlikely to be consistent between states and so this was avoided to maintain data validity and consistency. While auction locations are most dense in the Southeast, this area exhibits less of a climate signal in initial model runs, coastal auctions contain large portions of ocean in the market areas, and the practice of livestock production differs in many ways from that of the West.

Building the Data Set

To build the dataset and include the desired variables two main sources of information needed to be combined. From the original AMS dataset, downloaded text files are converted into data frames using pattern recognition in R, a statistical programming language that allows for a high degree of flexibility when manipulating data sets. Daily records are aggregated into monthly sums and arithmetic means depending on the variable. Cattle weights in the Central US exhibit skewness, as can be seen in the quantile-quantile plot above, therefore a log-transformation was applied and used for the dependent variable.

Climate index values needed to be standardized in order to interpret coefficients and standard errors with a common scale. Before standardization, though, it was necessary to adjust for outliers. Most of the drought indices have rare, anomalously high or low values, and while the rainfall index necessarily lacks outlying low values, it does have a very large amount of very high values. If these outliers were neglected, most of the variance in a standardized rainfall index would occur within a very narrow range close to zero and result in coefficients that are artificially larger than those resulting from the normal distributions of the drought indices. It would not be appropriate, however, to throw out every outlying value because they still represent either anomalously dry or wet periods.

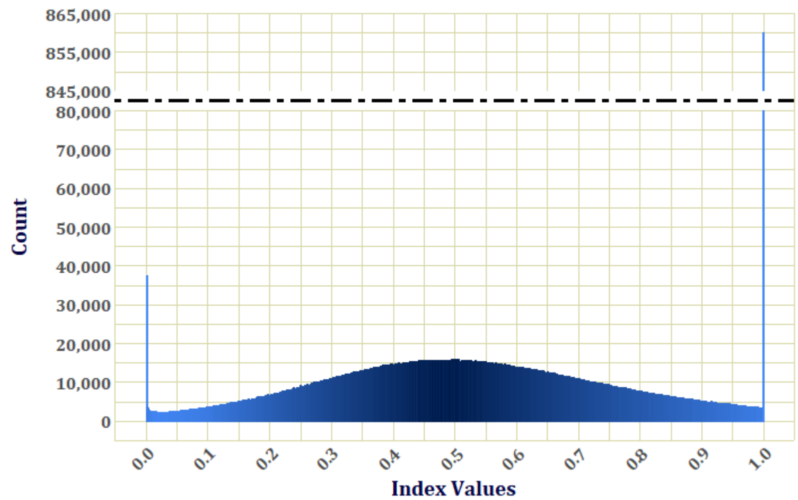

Figure 6. *The resulting value distribution of assigning outlying rainfall index values to that of three standard deviations above the mean and standardizing. A vast majority of values are considered outliers, and these result from heavy but less frequent rainfall events.*

Therefore, for all indices, values above and below 3 standard deviations of the mean were assigned the values of 3 standard deviations above or below the mean. The resulting mean values for each standardized index were centered on a value very close to 0.5, with the rainfall index centered on .505, precisely.

Each monthly market observation was then associated with a standardized index value for that location and time. Lagged independent climate variables were created for each observation so that each had a two-year history of drought conditions. These lagged variables were then associated with particular months of the year in order to more easily quantify the effects of prior growing season periods. To provide each observation with the full two-year record described above it was necessary to reduce the datasets study period by 2 years, so that the first observations begin in 2002. Because of heavy collinearity between monthly

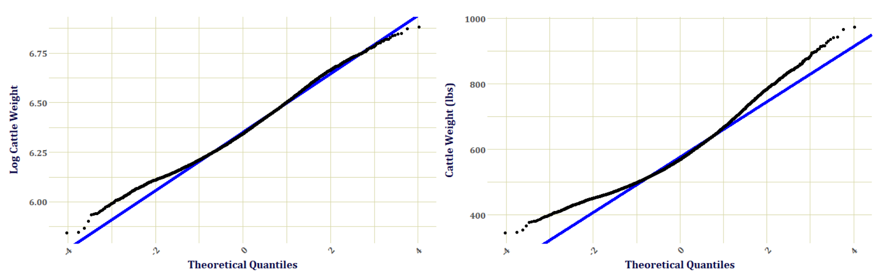

Figure 7. *Cattle weights were log-transformed to create a more normally distributed dependent variable.*

climate observations index values were aggregated by average values for the winter, spring, summer, and fall of both years.

Market Area Determination

Point estimates of climate at each auction were considered to be insufficient for association with market activity. Ranching requires a lot of land, and there are only so many auctions, so cattle production from potentially far distances will be represented by each. The most appropriate area in which to take drought index means should correspond, at least generally, with the area of cattle production that the data from a market reflects. There is some research on the general size of cattle market areas in the central United States and the most useful for this study are summarized here.

Bailey et al (1995) estimate market areas for livestock buyers in an attempt to better understand cattle market power imbalances. The areas were determined by the ultimate destinations of feeder cattle following sale, mainly feedlots, and the prices paid. 24,000 sale records of head counts, price, and county of destination were obtained from video auction data of four major cattle market centers in the Central U.S. between 1987 and 1992. These auctions were in Dodge City, KS, Amarillo, TX, Omaha, NE, and Greeley, CO. Though livestock sales are made freight on board with costs assumed by the buyer, transportation costs are expected to be reflected in the agreed upon price and this effect is considered an important determinant of the market area. To account for price differentials due to transport, costs were estimated using rates acquired via the livestock trucking industry. They then develop a unique statistic that estimates the proportion of buyers from particular counties for each auction as a function of buyer demand and county of destination. This proportion is used in a random effects regression analysis along with price to estimate general market areas around each of the four hubs.

The resulting buyer's market areas for each hub are dominated by many of the same locations across the central US, though there is an obvious effect of distance. These areas are very large, overlap significantly, and usually have irregular shapes, presumably due to competition between the market centers. The results show that the Omaha auction market area included Nebraska, Iowa, Indiana, Illinois, Minnesota, Missouri, Montana, North Dakota, and South Dakota. The Greeley area was perhaps most irregular including, in addition to Colorado, Michigan, Pennsylvania, and West Virginia. Dodge City's included Arkansas, Colorado, Kansas, Missouri, and Oklahoma. Amarillo's included Texas, Florida, Louisiana, New Mexico, and Oklahoma. This indicates that the buyer's market range for these most active sale hubs can extend as far as 2,000 km, but more generally falls between 500 and 900 km.

Buhnerkempe et al (2013) exploit a 2009 cross section of records on Interstate Certificates of Veterinary Inspection (ICVIs), which are required in most cases of livestock transport, to delineate a national cattle transportation network. They find that this network is dominated by several dominant hubs, and that the Central Plains region has the most connectivity which is associated with a well-developed feed infrastructure. Interstate transportation linkages are again shown to span large geographic distances, and the irregularities of their shapes of the networks are found to preclude the utility of aggregated state-scale structures.

Gorsich et al (2016) expand on Buhnerkempe et al's use of network analysis with a panel of ICVIs between 2009 and 2011 to identify communities of counties in which cattle shipments are clustered and any seasonal variation within them. A community is characterized by high numbers of network links within itself and low numbers of links between other communities, and is identified with a network detection algorithm. They discover that the number and distances of community links do vary by season, and there were consistent peaks in community sizes in both April and October, with troughs in July and December. The structure of the network linkages, though, are consistent from year to year and this is attributed to a fixed interstate infrastructure. Three major Central US communities of beef production transport were identified and these share similar extents as the 4 major market areas found in Bailey et al. The smallest is centered near Omaha, Nebraska and includes parts of Kansas, Missouri, Iowa, and Illinois. It is ovular with a semi-minor axis of about 350 km and a semi-major axis of 500 km. A large circular community with a general radius of 600 km in the northern states includes almost all of Minnesota, Montana, North and South Dakota, Wyoming, as well as northern portions of Colorado, Iowa, and Nebraska. The southern community is a more spread out, but has a center point near Amarillo, and the bulk of it includes Texas, Arkansas, Louisiana, Oklahoma, most of New Mexico, parts of SE Colorado, SW Kansas and smaller portions of Alabama, Arizona, and Mississippi. The general radius of the main grouping of this southern community is closer to 700 km. As did Bailey et al, these authors found isolated groups of counties as far as Southern Florida that were included in this community.

This literature exposes some complexity in the determination of Central US market areas; transportation networks can be very large with dense linkages, are often intertwined with one of several prominent hubs, are sometimes irregularly shaped, and vary in extent from season to season, though they are consistent from year to year. The distances that cattle producers are willing to truck their animals to sale are likely smaller than those of the buyers studied above; grazing operations are more densely and evenly distributed than feedlots and meatpacking sites. However, though rangeland conditions surrounding an auction will depend largely on the extent of local drought, the variance of weights at any individual market are related to fluctuations of feed and cattle prices within a large transportation network and are likely to exhibit signals of drought from far locations regardless of local conditions. Therefore, the climate signal in the AMS market data will reflect the effects of both local rangeland conditions and large-scale disruptions to other elements of the industry.

For the purpose of assessing an index for suitability in an insurance program, it would be preferable to distinguish the smaller-scale effects of local drought from the network-scale effects of distant drought. Also, while this analysis is concerned with cattle production, the distances detected in the network analyses above involve a different aspect of the marketing process; post-sale destination. In order to determine the most appropriate market area for producers reflected in the AMS cattle auction data, a corollary experiment was performed. This was based on the hypothesis that model fits and effects of local drought on cattle weights will rise continuously as the surrounding climate aggregation area increases until they reach the most appropriate distance, after which they will fall continuously. To test this theory datasets were created for each climate index by taking areal climate averages from increasingly larger radii around each auction. The same market data was associated with rainfall or drought index values averaged within 50 to 800 km radii in 50 km increments. For each of these 16 market areas, the two-way fixed-effects panel model analysis using the within estimator was performed. The magnitudes of growing season effects of the climate variables and total model fits for each dataset were expected to rise as the appropriate area was approached, and then diminish as the radius became too large, while the non-growing season effects were expected to be unresponsive to distance.

The presence of the expected pattern had to be continuous to be considered a peak. If the effects and fits rose or fell overall, but fluctuated on the way up or down, this was not considered indicative of the radius effect. With only 16 distance increments such a pattern might be attributable to random fluctuation. Some deviation from the trend was expected, but a series with more than two deviations from continuous rise and fall were not considered. Maximum values of continuous trends at the largest 800 km radius were not considered, though in some cases there was a distinct leveling off of the rate of coefficient increase that indicated a probable peak at 800 or 850 km. However, these were also not considered because of the uncertainty involved.

The initial model runs revealed that the pattern did indeed exists for the summer and spring months. Coefficients for the previous year's spring and summer also exhibited this pattern, though not as consistently. These were also the seasons that generated the most significant coefficients, with spring coefficients exhibiting the lowest p-values. Unexpectedly, winter effects sometime showed this pattern, but at much larger distances. The pattern was present most often at 700 to 750-kilometer radii for the one-month drought indices (Palmer Z Index, SPI-1 and SPEI-1), and likely reflects the influence drought on larger-scale industry practices, such as year-round grazing in the south and cooler weather feed crops. The model fit and growing season patterns indicated that peak climate effects appear at around 450 to 550 km, which corresponds well with the lower to middle range of the transportation network extents, but was a much larger distance than originally expected for the live-sale auctions. Adjustments to the original strategy were therefore required because this distance was a possible artifact of a particular limitation in the data and it was plausible that peak distances were even larger. Starting at about 300 km experimental market areas begin to cross US boundaries and by 800 km most of the southern and northern auction areas include significant portions that are either ocean, Mexico, or Canada, none of which are represented in the climate datasets. As market areas increased it was possible that effects and model fits diminished due to the presence of increasingly higher non-value counts. Therefore, to determine an appropriate market area, only the 50 most central auctions were used, the experimental market areas of which are nearly fully contained within the CONUS even at 800 km. There is some boundary crossing, but there are very few market areas that

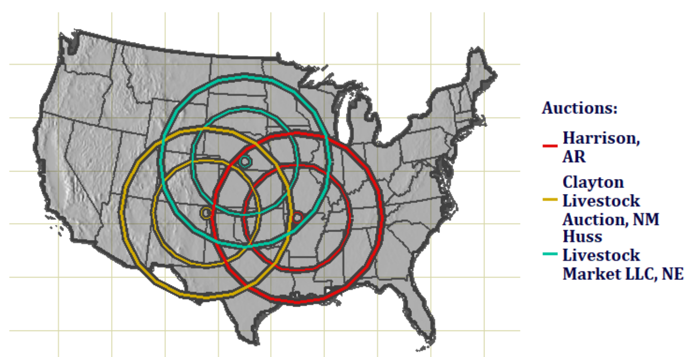

Figure 8. *A sample of three of the 50 central auctions and three of the 16 market areas, 50, 500, and 800 km, used to determine the appropriate market area.*

are 100% contained and this was considered acceptable because the overlap is negligible. This is demonstrated with three of the northern- and southern-most auctions in Figure 8.

Because market areas are not likely to be uniform from place to place it would be ideal to run regressions for each location and use the index values from each locally specific optimum aggregation area. However, the boundary problem precludes this strategy, so instead a generally representative market area as determined by these central auctions was sought.

The resulting coefficients and model fits from this reduced analysis still indicated that the most representative market area is between 450 and 550 km (Figures 9 & 10). Though the value differences between distances were slight, they were very distinct and fit the expectation. Nearly every model had fits that peaked within this range, though peak effects varied significantly by season. While the significance of effects are strongest in the spring, the pattern of the peak effects was strongest for the summers, followed by spring and winter. The fall effects of either the first or second previous year rarely even resembled this pattern. Generally, as in the initial model runs, winter peaks occurred at larger radii and there were seven of these. Most of the observations that did not exhibit a peak effect within the maximum study distance either rose or fell consistently and it was surmised that a larger-scale effect

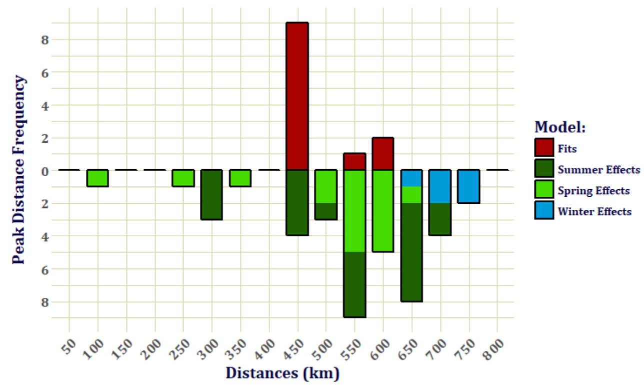

Figure 9. *Peak model fits occurred most consistently at 450 km while peak variable effects occurred at somewhat larger distances and depended on the season.*

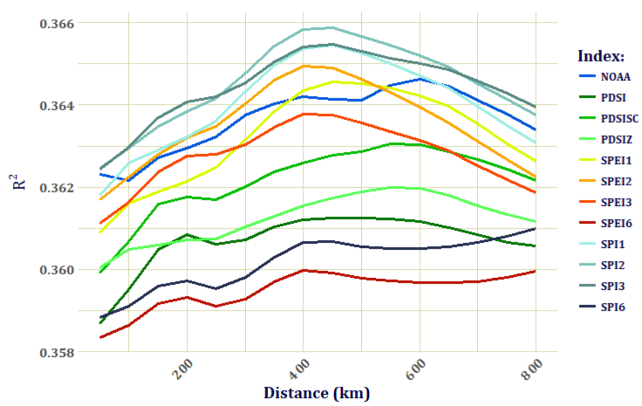

Figure 10. *Patterns of rising and falling model fits as the climate data aggregation radius increases. Overall model fits varied much less than effects, and their peak values depended somewhat on the index, though are generally centered around 500km.*

was at play. Monthly effects that peaked likely explain cattle weight variation due to local conditions, while those that continuously rose probably would have peaked at some larger radius and, considering the size of a 1,600 km diameter circle, likely indicate the effect of a national-scale phenomenon. The presence of winter peaks at larger radii may indicate regional-scale effects of drought. This would indicate that the summation of regional-scale droughts will cause local prices to fall, and that any measure of drought or precipitation over an increasingly wide radius will increasingly explain this effect.

It was also possible that the peak effects seen for each index were related to spatial qualities of the index itself. If drought or rainfall indices consistently exhibit correlated variance up to similar distances as the observed peak model effects this might indicate that the spatial extent of drought is a contributing factor. To test for this scenario 16 spring and 16 summer rasters, two for each study year, were chosen for each index and the ranges of their semivariance was calculated and compared to the peak effect distances. Each raster variogram was fit using an optimizing function in the R package "gstat" (Pebesma and Wesseling, 1998). Using this function initial model parameters are calculated as 1/3 of the largest variogram distance for the range, the average of the first three semivariance values for the nugget effect, and the mean of the final five semivariance values for the sill. To determine the most suitable range where variability levels off, each of these variograms are fit to either a spherical, Gaussian, exponential, or Matern model distribution, depending on which fit best. Spring and summer were chosen because these are the seasons for which the climate signal was both expected and observed to be strongest.

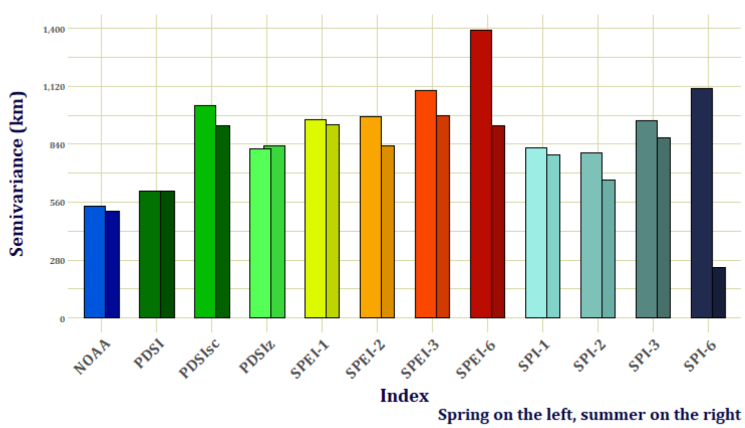

Figure 91. *Average ranges of semivariance ceilings with outliers removed.*

The results of this assessment do show some evidence of a relationship between the ranges of semivariance seen in the drought indices and the peak effect distances observed in the regression analysis (Figure 11). Ranges vary significantly from year to year, with some indices in some years exhibiting severe spikes in distance for all indices. These spikes are unreasonably high and are most definitely artifacts of the model fitting process, but occur consistently between the summer and fall indices and likely indicate periodic drought extents without a discernible sill of semivariance according to any of the models fitted. When these outlying years are removed some consistent patterns emerge. The most notable is that summer ranges are typically somewhat shorter than spring ranges, excepting the rainfall index, PDSI, and Palmer Z Index. This matches the general seasonal pattern of coefficient peaks discovered from the models. The two 6-month indices (SPI and SPEI) both show an large difference between spring and summer, which may be related with the spatial pattern seen in their model fits whereby an initial peak occurs at 400 km before rising beyond the study range. Generally, as the time-scale of the multi-scalar indices increase, do does the range of spring variance, though this is not true for the summer. Notably the precipitation index has a much smaller range of semivariance compared its peak radius found by the regression analysis. This is curious because this index had a peak model fit at 600 km, and peak coefficient magnitudes at even higher radii, while all of the farther ranging drought index models peaked at shorter distances. This value may also be related to the small 400 km peak that the rainfall and 6-month indices had before continuing to rise.

These patterns suggest that there may well be an inherent effect of precipitation on cattle weights up to the 500 km range, and the variance in effects between seasons might be related to the seasonality of the index of choice. However, the patterns discovered in the semivariance ranges do not fully explain the consistent discovery of a roughly 500 km threshold distance. For the majority of the indices, their effect on weights levels out far before the average extent of drought index semivariance, while the opposite is true for precipitation.

Specifying the Model

To specify the most appropriate model structure, pooled ordinary least-squares (OLS) models were created and the residuals were checked for fixed or random effects in each of the predicting indices. Breusch-Pagan Lagrange Multiplier (BP LM) tests for unbalanced panel models (Breusch and Pagan, 1980) consistently showed that there were significant time- and location-specific effects, justifying the use of a panel model estimation strategy and a two-way effects model that includes time. The Hausman specification test showed that there were significant correlations between the OLS error terms and the regressors, so a fixed effects model was chosen over random effects.

After applying the within estimation to the model, the BP LM tests for cross-sectional correlation and the Breusch-Godfrey tests for serial correlation (Breusch, 1978; Godfrey, 1978) were still significant, as was the BP test for heteroskedasticity (Breusch and Pagan, 1979), warranting the clustering of standard errors by location. This was performed with heteroskedasticity- and serial correlation-robust clustered standard errors using the Huber-White method described in section 3.1.

Results

The resulting model is able to predict cattle weights given price information and a 2-year monthly climate record with some skill. However, across models, there is very little difference between fits (table 1). Overall, each model explains either 79.0 or 79.1% of the variance in cattle market weights with root mean squared errors between 0.0652 and 0.0654. There is much more variation in coefficients and robust standard errors, with the strongest spring effects detected by the PDSI-SC, 1-month SPEI, and 1-month SPI. The strongest summer effects also arise in the 1-month SPEI and SPI. In fact, all of the one-month indices (rainfall, Palmer Z Index, SPEI-1, and SPI-1) show stronger summer time effects than those with more climate memory. This might suggest that, because these indices capture short-term climate fluctuations, they are also detecting a more local-scale effect, though this is uncertain. Interestingly, the significance of effects on the growing season periods of the second year prior to sale are often negative, excepting only the two Palmer Drought Severity Indices in the spring. This might suggest a rebound effect on the part of rangeland managers recovering from lost revenues in the previous year as their range recovers and they compensate with added supplementary feed or grazing pressure. It could also suggest that, simply, most of these indices are not capable of detecting any legacy effects of rangeland damage in particular. In either case, the levels of significance on these seasonal effects indicate some response to climate. In contrast, both of the PDSIs exhibited the strongest positive effects from spring index values in both years, perhaps indicating the detection of grassland productivity during the critical initial growth phase of grasslands.

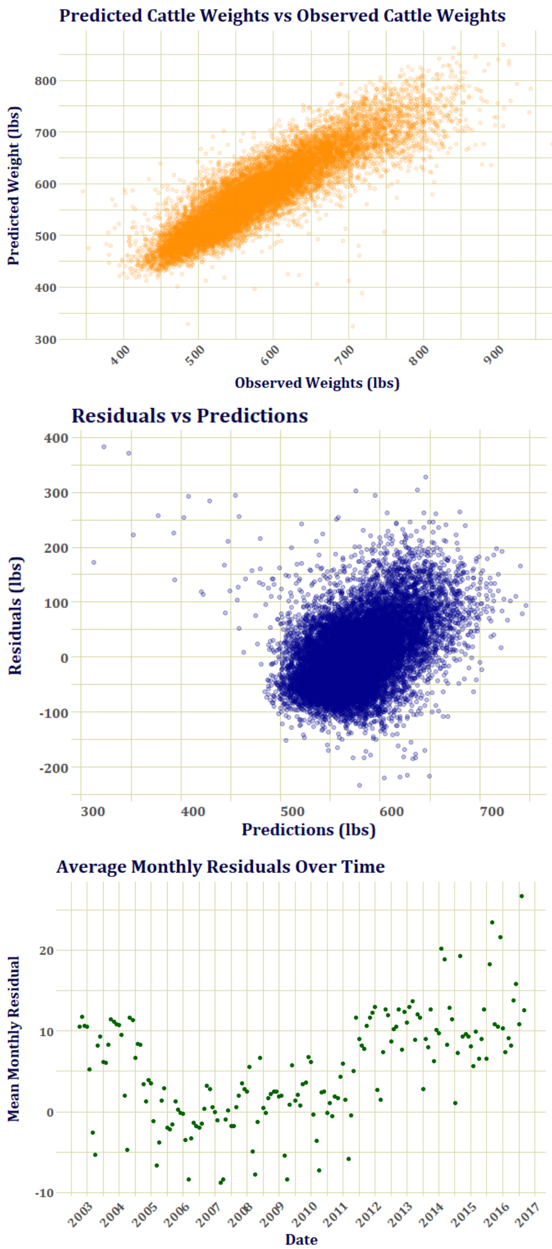

Figure 12. *Overall model residual structures showing relationships between predicted and observed values, residuals and predicted values, and residuals over time.*

Model residual structures are very similar between indices so only those of the rainfall model are displayed here. In Figure 12**,** prediction and residual relationships are exponentiated back into pounds and plotted to help with interpretation. Nationally, the model predictions vs observed plot shows a distinctly linear relationship, though the plot of residuals vs predictions reveals that the model tends to over predict at the low and high ends of the cattle weight range. A time series of average monthly model residuals shows significant

500 km Regression Results - Two-Way Fixed Effects

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Rainfall	PDSI	PDSI-SC	Z Index	SPI-1	SPI-2	SPI-3	SPI-6	SPEI-1	SPEI-2	SPEI-3	SPEI-6
VARIABLES	Log Weight	Log Weight	Log Weight	Log Weight	Log Weight	Log Weight	Log Weight	Log Weight	Log Weight	Log Weight	Log Weight	Log Weight
Constant	4.4865***	4.4866***	4.4823***	4.4978***	4.4664***	4.4740***	4.4702***	4.4896***	4.4664***	4.4658***	4.4665***	4.4837***
	(0.1340)	(0.1383)	(0.1378)	(0.1347)	(0.1320)	(0.1336)	(0.1351)	(0.1384)	(0.1334)	(0.1347)	(0.1366)	(0.1389)
Log Weight$_{t-12}$	0.3219***	0.3240***	0.3240***	0.3233***	0.3233***	0.3217***	0.3212***	0.3205***	0.3252***	0.3233***	0.3222***	0.3203***
	(0.0184)	(0.0186)	(0.0186)	(0.0187)	(0.0186)	(0.0185)	(0.0185)	(0.0189)	(0.0186)	(0.0187)	(0.0187)	(0.0189)
Price	-0.0028***	-0.0028***	-0.0028***	-0.0028***	-0.0028***	-0.0028***	-0.0028***	-0.0029***	-0.0028***	-0.0028***	-0.0028***	-0.0029***
	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0004)
Index Values:												
- Month of Sale	0.0043	0.0943***	0.1419***	0.0153*	0.0031	-0.0015	0.0135	0.0865***	0.0092	0.0089	0.0270**	0.0997***
	(0.0052)	(0.0111)	(0.0165)	(0.0088)	(0.0077)	(0.0100)	(0.0106)	(0.0118)	(0.0077)	(0.0100)	(0.0106)	(0.0115)
- Winter$_1$	0.0482***	-0.0410**	-0.0737***	0.0549**	0.0724***	0.0430***	0.0116	0.0342**	0.0542***	0.0382***	0.0051	0.0238
	(0.0121)	(0.0163)	(0.0253)	(0.0267)	(0.0181)	(0.0141)	(0.0131)	(0.0170)	(0.0188)	(0.0146)	(0.0137)	(0.0192)
- Spring$_1$	0.0607***	0.0766***	0.1107***	0.0636***	0.0796***	0.0658***	0.0798***	0.0382**	0.0790***	0.0654***	0.0760***	0.0349*
	(0.0141)	(0.0193)	(0.0275)	(0.0182)	(0.0187)	(0.0142)	(0.0136)	(0.0179)	(0.0190)	(0.0148)	(0.0145)	(0.0194)
- Summer$_1$	0.1255***	-0.0076	0.0053	0.0903***	0.1733***	0.0958***	0.0439***	0.0524***	0.1410***	0.0800***	0.0400***	0.0427**
	(0.0149)	(0.0154)	(0.0229)	(0.0153)	(0.0204)	(0.0162)	(0.0137)	(0.0172)	(0.0193)	(0.0153)	(0.0129)	(0.0182)
- Fall$_1$	0.0050	-0.0441***	-0.0696***	-0.0021	0.0062	0.0575***	0.0872***	-0.0499**	0.0250	0.0565***	0.0778***	-0.0405*
	(0.0151)	(0.0152)	(0.0220)	(0.0250)	(0.0230)	(0.0176)	(0.0155)	(0.0201)	(0.0244)	(0.0191)	(0.0167)	(0.0207)
- Winter$_2$	-0.0260**	-0.0512***	-0.0776***	-0.0410	-0.0412**	-0.0270*	-0.0308**	-0.0178	-0.0378*	-0.0243	-0.0280*	-0.0211
	(0.0122)	(0.0169)	(0.0256)	(0.0263)	(0.0191)	(0.0162)	(0.0154)	(0.0234)	(0.0192)	(0.0163)	(0.0158)	(0.0249)
- Spring$_2$	-0.0167	0.0296	0.0273	-0.0488***	-0.0320**	-0.0264*	-0.0164	-0.0197	-0.0504***	-0.0395***	-0.0254	-0.0160
	(0.0107)	(0.0224)	(0.0332)	(0.0149)	(0.0135)	(0.0142)	(0.0159)	(0.0240)	(0.0140)	(0.0149)	(0.0170)	(0.0241)
- Summer$_2$	-0.0465***	-0.0471**	-0.0671**	-0.0308*	-0.0636***	-0.0314*	-0.0266*	0.0096	-0.0611***	-0.0304*	-0.0274*	-0.0084
	(0.0145)	(0.0191)	(0.0282)	(0.0165)	(0.0191)	(0.0163)	(0.0154)	(0.0209)	(0.0178)	(0.0155)	(0.0157)	(0.0224)
- Fall$_2$	-0.0593***	0.0263	0.0465*	-0.0627**	-0.0951***	-0.0725***	-0.0480**	-0.0521**	-0.0909***	-0.0663***	-0.0426**	-0.0312
	(0.0163)	(0.0161)	(0.0244)	(0.0281)	(0.0251)	(0.0218)	(0.0203)	(0.0205)	(0.0257)	(0.0230)	(0.0212)	(0.0210)
Observations	14,933	14,933	14,933	14,933	14,933	14,933	14,933	14,933	14,933	14,933	14,933	14,933
Number of id	140	140	140	140	140	140	140	140	140	140	140	140
RMSE	0.0653	0.0653	0.0652	0.0654	0.0652	0.0653	0.0653	0.0653	0.0652	0.0653	0.0653	0.0652
Rho	0.618	0.614	0.614	0.613	0.614	0.617	0.615	0.611	0.613	0.616	0.617	0.615
Within R-squared	0.385	0.384	0.386	0.382	0.385	0.383	0.383	0.384	0.386	0.384	0.383	0.385
Between R-squared	0.842	0.837	0.834	0.847	0.844	0.842	0.849	0.843	0.847	0.841	0.840	0.834
Demeaned Model R-squared	0.544	0.550	0.552	0.550	0.551	0.545	0.548	0.554	0.552	0.545	0.544	0.549
Full Model R-squared	0.791	0.791	0.791	0.790	0.791	0.790	0.790	0.790	0.791	0.790	0.790	0.791

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 1. *Model summaries using each of the 12 indices examined in this analysis. Statistics include coefficients and standard errors of independent variables, root mean squared error, and model fits for the within estimation, between estimation, the full demeaned model, and the full-none demeaned model.*

inconsistency over time. While residuals are relatively well centered on 0 between 2005 and 2011, they over predict in the several years prior to 2005 and following 2012. These periods are associated with significant drought in major cattle producing areas, and indicate a serious sensitivity that even the drought indices cannot account for.

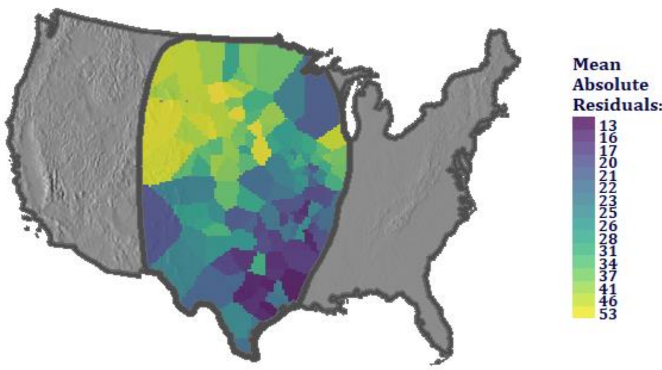

Figure 10. *Mean absolute residuals as Voronoi polygons around each auction showing a significant southern bias in the performance of the model.*

Exponentiated residual values are also averaged and mapped as Voronoi polygons around each auction to check for spatial trends in the performance of the models (Figure 13). The resulting spatially averaged residuals range from 13.2 to 64.3 pounds, with an increasing gradient of absolute residual magnitude from the southeast to the northwest portions of the study area.

In order to illustrate the performance of the model on a local scale, average monthly residuals from each of a four-auction sample were plotted over time and displayed in Figure 14. These auctions were chosen because they represent individual auctions with relatively high sales at different latitudes. They include the Billings Livestock Commission in Montana, the Huss Livestock Market LLC in Nebraska, the Coleman Livestock Auction in Texas, and the Oklahoma National Stockyards in Oklahoma City, which experiences by far the most sales of any of the auction in the study area. Montana was chosen because it represents cattle ranching in a mountainous and northern region, where residuals are particularly high. In contrast to the model performance as a whole, these time-series exhibit fairly consistent variation over time. There does appear to be a somewhat negative trend at the Texas auction, and the Nebraska auction residual ranges appear to expand somewhat near the end of the study period, though these discrepancies are slight. Just as the overall model residual map indicates, the farther north the auction is the larger these local average residuals become.

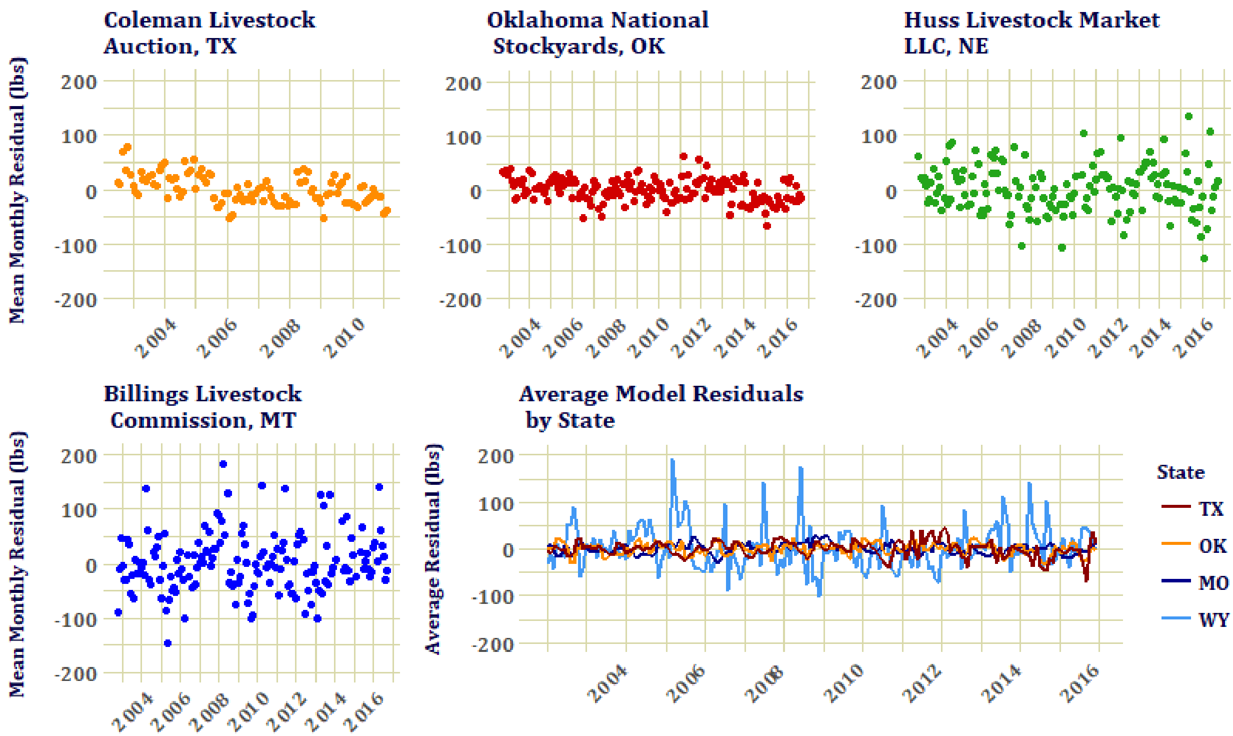

Figure 11. *Mean monthly residuals at each of four auction sites chosen for their regional sale magnitudes, along with a time series of average monthly residuals for four of the most active cattle ranching states.*

Also, average residuals from Texas, Missouri, Oklahoma, and Wyoming were generated to further illustrate differences between locations, but on a broader scale. A time series of these are also included in Figure 14. These show that the model performs relatively well in the southern states, though there is some disturbance in Texas following 2012. The residuals in Wyoming show that there are severe spikes in over predictions during the growing season sale months with some troughs of under predictions in the fall and winter sale seasons, indicating that the 12-month lagged weight term did not sufficiently account for the seasonal variation in cattle weights in the northern auctions.

Discussion

Through this analysis a very clear climate signal was revealed in the fluctuations of weights in cattle market data. This came in the form of expected significant positive effects on cattle weights during the growing season months, expectedly insignificant effects during the winter and fall, and unexpectedly significant negative effects on values during the growing season of the second year prior to sale. This last point still serves to increase confidence that detection of a true climate signal has been made because it is very unlikely that this pattern would arise at these times of the year if it were not for some climate response. A relationship between the effects of drought and rangeland productivity is documented in the literature (Griffin-Nolan et al, 2018), with at least one study which discovered a similar temporal pattern when examining the effects of precipitation on NDVI values in the grasslands of the Central Plains (Wang et al, 2003). However, the signs of the coefficients are most often opposite of what would be expected given this theory, which indicates that there may some sort of reactionary effect in the decision making of ranch managers attempting to recover lost revenues in the subsequent year. If any of the drought index is detecting second year effects of lost rangeland productivity, it would be the Palmer Drought Severity Index, which detects significantly positive effects in the spring months of both years.

The differences in model fits and coefficients on seasonal index values were too small to serve as evidence that any one of these indices better predicts the impacts of drought in the cattle ranching industry of the Central US than any other. A look at the residual structures and predictions resulting from each of the indices tested reveal that they are estimating basically the same model. It would appear as though precipitation is responsible for the large majority of drought effects on market weights.

The relationships between weights, cattle prices, feed prices, rangeland productivity, and a very large, highly interconnected central US feed and livestock transportation network mean that this model is capturing much more than a local climate effect. Rather, it is predicting a cumulative effect of a complex system. This could indicate that any potential specificity gained over simple rainfall by the use of a drought index for monitoring market impacts is diluted by the scale of market activity. It could also mean that these gains are simply slight to begin to with. Because each index indicates both wet and dry conditions, it could also indicate that the cattle market is unexpectedly sensitive to heavy rain events and a better model would use a method to isolate drought events. Of course, the use of a two-way fixed effects model, which by design removes a significant amount of information and variance from the data, might not be the most appropriate method for capturing small scale drought effects and comparing the performance of indices. At the same time, the method is very common and accepted, and none of the drought indices performed any worse than the rainfall index. So, while these results cannot indicate a preferable drought index for use in the PRF, none can be ruled out. This leaves a large degree of flexibility when attempting to reduce temporal basis in this much smaller-scale application.

CHAPTER IV

DROUGHT INDEX INSURANCE EXPERIMENTS

Even if rainfall is the primary determinant of cattle market-wide drought impacts, as the above analysis suggests, problems remain with its use in local-scale risk protection. Insurance using the RMA rainfall index creates a significant possibility of non-payment following desiccation of a range and tends to pay more in the winter and fall seasons. Because the PRF does not allow for coverage throughout the entire year and leaves the choice of which seasons to insure up to the policyholder, this latter feature incentivizes non-growing season protection. Together these features lead to risks of both non-payment when there was genuine rangeland damage, and payment when there is no need.

Considering the amount of complexity, effort, and policy design required to adjust rainfall into an index that accurately predicts plant response to drought, as well as the difficulty that would arise in the explanation of that index's functionality to potential policyholders, it is worth considering the use of a drought index specifically designed for this purpose. In this chapter the drought indices used in the market analysis are used as experimental alternative indices within the structure of the PRF to examine the timing, magnitude, and seasonality of simulated payouts. Because each of the drought indices explained a very similar amount of cattle market drought impacts in chapter 3, each one is used to compare with the rainfall index and each other.

Rationale for Drought Index-Based Insurance

Why doesn’t the RMA use a drought index to insure against drought-related losses in the US livestock industry? Ironically, while the appeal of index-based insurance and the efficiencies it affords was bolstered by the difficulties of Federal Crop Insurance Program, the lack of interest in drought index-based insurance appears to be founded in an aversion to the multi-peril protection provided by this same program, despite the potential to address the difficulties experienced with rainfall. When asked why the RMA does not use the popular US Drought Monitor (USDM) in place of the rainfall index, they explain that this product includes multiple measurements to categorize drought and therefore would not be appropriate because the PRF is a “single-peril program” (RMA, 2017a). There are other reasons why the USDM would be difficult to use in this application; namely, because it is not technically an index. Instead it is a broad and categorical description generated from the combination of *both* quantitative drought indicators and the professional, but necessarily qualitative, observations of various regional experts (Svoboda et al, 2002). If it was to become intertwined with potential financial gain from indemnification, the qualitative aspect of this product could potentially undermine the critical assumption of independence in the loss-metric. Because it is not indexed, a USDM-based description of drought is not necessarily relative to normal conditions for a particular location and time of year. Though it could be indexed, further difficulties would arise because it is not generated along a continuous scale and its period of record extends only to the year 2000. While it might be possible to account for the former quality (see Lorenz et al, 2017), this latter quality would result in baseline values that consider the last two drought-ridden decades as normal, making payouts less likely. However, none of these reasons were explained as justification for the avoidance of the USDM, and the problem of multi-peril risk remains as the most likely reason.

Like the USDM, most drought indices are also calculated using multiple variables, though these are always quantitative, continuous, and usually have long histories. They typically include at least precipitation and temperature, but sometimes other variables such as wind speed and relative humidity. Even if a singular index value is generated using these products, they do represent many factors and so might also be perceived as representing multiple perils. While factors such as these are critical to plant productivity, a single-peril insurance plan is perceived as a much safer option; the RMA, as described earlier, had significant difficulty insuring against multiple sources of loss in the crop industry.

However, the practice of multi-peril, or “all-risk”, insurance should not be conflated with a multi-factor risk insurance product that could be developed around a drought index. The various factors that are involved in the calculation of the drought index are integrated and each is important to determining a singular value for water deficiency, the underlying peril to plant production. Without the incorporation of temperature, the index ignores the main cause of water loss in grasslands: evapotranspiration. Also, drought will be perceived as a singular phenomenon by most policyholders and, importantly, there is no research to indicate that a drought index would be costlier than a rainfall index in an insurance application. Actually, it is quite possible that significant cost efficiencies could be gained by a reduction in basis risk and the added participation that it would encourage.

Also, the use of a drought index to monitor drought conditions is common in agricultural communities, especially for the ranching community which relies on rainfed forage and must maintain increased preparedness for drought. Because agriculture is especially vulnerable to drought, many drought indices are designed around, and well-suited to, describing agricultural impacts. While a drought index cannot account for every local specificity and will still exhibit imperfect correlation with productivity, agriculturally-oriented indices will, by design, better reflect vegetative drought impacts. Some will perform better at this task than others overall, and some will perform better in certain places.

Because most drought indices use only precipitation and temperature they are able to take advantage of historical US climate record-keeping and provide long-term averages comparable to the PRF's rainfall index. Also, because they are indexed to local and seasonal baselines like the rainfall index, they represent comparable levels of probable impacts across locations and times of the year.

While there are several new remotely-sensed products, including the Gravity Recovery and Climate Experiment (GRACE) and the Soil Moisture Active Passive satellite (SMAP), which could provide more precise information of soil moisture conditions and likely serve as better indicators of plant production, their lack of long historical records would preclude their use in an insurance setting. With a record of only a decade or two, an index based on satellite observations would not reflect deviations from a long-term climatic norm.

The PRF is the largest weather-based insurance program in the US making it a suitable representative of the practice. Because it is a public program the mechanics of its functionality are open and simple to discern, and because it is part of the long-running Risk Management Agency it has a well-developed actuarial system. Also, because rainfall is the primary determinant of drought, this index-based program provides both a suitable platform upon which to test the behavior of a drought index in an insurance setting and a functional baseline with which to compare the payout distributions generated by different indicators.

Pasture, Rangeland, and Forage Program Description

The PRF is a cumulative rainfall-based index insurance program that is provided through the US Department of Agriculture's Risk Management Agency (USDA-RMA), and is designed for loss mitigation in both grazing livestock and hay production, though only grazing is examined here. The index values represent proportions of observed rainfall to long-term averages. They are derived from daily rainfall data via a product of the National Oceanic and Atmospheric Agency's (NOAA) Climate

Prediction Center (CPC) called the Unified Gauge-Based Analysis of Daily Precipitation over the Contiguous United States.

Rainfall Index Description

The Unified Gauge-based Analysis gridded precipitation product from which the index is derived is based entirely on data from US weather reporting stations. It is calculated using an algorithm designed around the "optimal interpolation" method of Gandin (1965) which is intended to account for inaccuracies in areas with sparse data sources and orographic effects. The "unified" part of the product title refers to a large-scale effort by NOAA to standardize data collection methodologies used in world-wide CPC reporting stations to take advantage of as many stations as possible and improve accuracy and consistency.

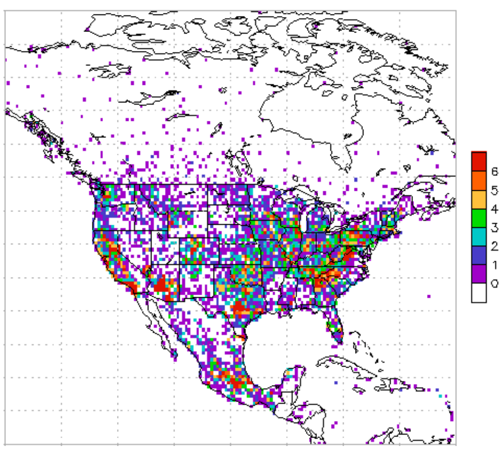

Figure 12. *The US has one of the densest weather data collection networks in the world, though many areas have no stations within many miles.*

The gauge-based analysis is derived from a dense collection of weather reporting stations; however this density varies over space and many locations have no weather stations within many miles. This is particularly true in the mountainous areas of the West. While remotely sensed methods based on imagery or radiation can estimate moisture across the entire surface, precipitation estimates made using these methods use land surface dynamics models and so cannot be considered direct observations. They also have a much shorter historical record than the gauge-based data and this is important to consider when indexing against long-term baselines. Also, considering that interpolation quality improves with data station density and that the US has one of the densest networks of meteorological stations in the world, the gauge-based analysis is likely the most accurate method of US rainfall quantification available.

The data is originally recorded as millimeters per day and interpolated to a 0.25- by 0.25-degree grid, which translates into roughly 13 square km, depending on the latitude. The RMA then aggregates this daily data into 2-month averages, resulting in 11 overlapping bi-monthly intervals (Jan-Feb, Feb-Mar, etc.). There is no overlap between December and January to reflect a calendar-year insurance policy period. Baseline average values for each cell and each bi-monthly interval between 1948 and 2-years prior to each insurance year are then used to derive the index. An index value, therefore, reflects the percentage of the 1948-to present average precipitation for a specific location and a specific bi-monthly interval.

Indemnification Process Description

Policyholders will receive a payout only if the two-month rainfall index value falls below a certain percentage of the average value for that grid cell. The percentages of average rainfall that can trigger a payout range from 70% to 90% in 5% intervals, and are chosen by the policyholder in advance of the insurance year. These percentages are referred to variously as “guarantee”, “coverage”, or “strike” levels, and are chosen by the policyholder upon purchase for the up-coming insurance year. The government subsidizes premiums at rates dependent on the strike level, with the lowest level receiving 59% subsidization and the highest 51%. Higher strike levels increase premiums and decrease subsidies, but also increase the chance of payout and the total dollar amount of protection available. The degree to which a present index value falls below the baseline average value is also taken into account when determining the payout, so that, for example, an index of 30% of baseline pays more than one of 50%. This ratio is referred to as the “payment calculation factor” (PCF) and is calculated as the difference between the strike and observed rainfall level, divided by the strike level for observed values below the strike level:

$$Payment\ Calculation\ Factor\ =\ (Strike\ Level\ -\ Index)\ /\ Strike\ Level\ ,$$

where,

$$Index < \ Strike\ Level$$

Therefore, higher strike levels increase both the chances and magnitude of payouts. Additionally, the policyholder must choose how to allocate coverage over the eligible bi-monthly intervals for each insurance year. These intervals overlap such that the first includes January and February, the second February and March, and so on. December and January do not overlap resulting in 11 intervals per year. One hundred percent of the total coverage chosen by the policyholder must be split between these intervals, however consecutive intervals may not be chosen because that would result in insurance of the same month twice. Also, RMA sets limits to the proportion of coverage that can be placed in any one interval, with a consistent minimum of 10% and a maximum that ranges geographically from 50% in the South to 70% in the North. For counties in California and Arizona, many intervals are not eligible at all. The RMA encourages policy-holders to place coverage in the intervals in which rainfall is most important to their local forage production. For example, 30% of coverage could be allocated to the March-April interval, 30% to May-June, and 40% to July-August, which are peak growth periods for many regions.

The total amount of possible protection for a given interval is representative of both the productivity of the land and the value of the policy itself. A per-acre dollar value is set for each county, and referred to as the base rate. This value is typically fairly low in the western states, and much higher in the East where carrying capacities are higher, and ranges from $5.50 per acre in counties of Utah and Wyoming to $109.80 in Pennsylvania. These values are fixed throughout the year. A policyholder can also adjust the protection amount by incorporating the perceived productivity of their land, sometimes splitting policies between more and less productive portions. This is incorporated by scaling the protection amount with by variable called the "productivity level," which ranges from 60 to 150%. That product is then multiplied by the portion of total coverage allocated to the interval in question and the bi-monthly protection amount becomes:

$$Protection\ = County\ Base\ Rate\ * Acres * Strike\ Level\ * Productivity\ Level\ * Allocation$$

When the index falls below the strike level this protection amount is adjusted by the payment calculation factor to generate the payout amount or indemnity:

$$Indemnity\ =\ Payment\ Calculation\ Factor\ *\ Protection$$

Premiums are calculated by scaling the protection amount with a premium rate that depends on the grid location, bimonthly interval, chosen strike level, and often the county of the policy if a grid cell overlaps two or more. These rates range widely from 0.46% in Polk County, FL, to 65.25% in La Paz County, AZ. The total premium amount is the yearly sum of the protection values for each interval chosen as scaled by their respective premium rates. The bi-monthly premium paid by policyholders is the difference after the subsidy is subtracted:

$$Producer\ Premium\ = Protection\ *\ Premium\ Rate\ - (Protection\ *\ Subsidy\ Rate)$$

Alternate Index Experiment

Whereas the market analysis in chapter 3 sought to analyze the ability of various drought indices to capture the socio-economic impacts of drought, this analysis seeks to assess their ability to reduce temporal basis risk in the PRF and to assess the performance of alternative indices. To do so a simulation of the rainfall index and the structure of the PRF are used to create a time series of potential PRF payouts for every location in the contiguous United States. These potential values are represented in dollar amounts of insurance payouts that would have occurred for each bi-monthly interval under the same policy for each location with actuarial rates set by the RMA for the 2018 insurance year. The project then examines how payouts would be distributed if the insurance program used an alternative drought index in place of the rainfall index. Indices to be tested include the Palmer Drought Severity Index (PDSI), the self-calibrated Palmer Drought Severity Index (PDSI-SC), the Palmer Z Index (Z Index), the 1-, 2-, 3-, and 6-month Standardized Precipitation Indices (SPI), and the 1-, 2-, 3-, and 6-month Standardized Precipitation Evapotranspiration Indices (SPEI). Payout distributions based on the different indices are also compared for seasonality of payment trends.

Methods

To simulate the Pasture, Rangeland, and Forage payouts, actuarial information was acquired through the Risk Management Agency's information browser for the 2018 insurance year (USDA-RMA, 2018b). Rainfall index, indemnity, and premium calculations were validated using the PRF decision support tool available through the RMA's website (USDA-RMA, 2018c). Historical loss ratios and participation rates were derived from summaries of business reports, also available through the RMA's website (USDA-RMA, 2017b).

To compare the behavior of the PRF using alternate drought indices, drought index raster datasets of the contiguous US were resampled to 0.25-degree cell sizes and index values at each cell were combined into overlapping bimonthly means to match the spatial and temporal structure of the RMA's rainfall index. Time-series of index rasters were converted into 3-dimensional arrays in Python to more efficiently perform cell-wise insurance calculations for each grid cell in the continental US. Each cell was associated with the appropriate RMA grid ID and actuarial information. Premium rates, base county values, and bi-monthly allocation limits for each grid cell were associated with the appropriate index cell and month. To replicate the rainfall index, original mean daily values were binned into bi-monthly intervals and each of these values were divided by the long-term average for each location and interval calculated from the period between January of 1948 and December of 2016. This results in a non-normal distribution of values between 0 and 4,161% with a heavy right skew, a modal value range between 0 and 0.003%, and an uptick in probability as values approach this first bin as can be seen in Figure 16. While 100% is considered a normal value with this indexing method, because of the skew it is not the most common value which is actually around 80% (after 0%). The presence of such a high number of low values results in a higher chance of payment triggers, larger payment calculation factors, and, therefore, larger overall payments compared to an index with a normal distribution.

Necessary adjustments

To allow the PRF to accommodate the various indices it was necessary to make some adjustments to both. These adjustments were as minor as possible in order to maintain the structures of both the PRF and each index. Drought index value distributions differ drastically from that of the rainfall index. Most are, by design, highly normal and centered around 0 with negative values indicating drought and positive values indicating wetter than normal conditions. Extreme low values do occur from time to time. For example, the SPEI-2 generally ranges from about -2.5 to 2.5, but has had exactly two values below -7 since 1948. Both of these happened within an anomalous pocket of low index values in Pecos County, Texas during the third interval of 2011, representing a concern that, on occasion, incredibly high payouts could result from drought index-based insurance. These outliers are also reflected in the original value distributions and affect the appropriate strike levels. The issue is somewhat moderated when monthly values are averaged into bi-monthly bins, but is still problematic, particularly for the SPEI-3 and the PDSI. It would not be appropriate to simply remove these outliers from the index because they still represent extreme drought and each month requires a value. Therefore, values above and below three standard deviations of the average of each index were assigned the values at three standard deviations above and below the average.

Remaining differences in index value distributions also change the strike levels that are appropriate for each index. The rainfall index is based on a ratio of current rain to the historical average and so results in percentages. It might be possible to simply apply the same indexing method used for rainfall to recalculate each drought index with their own historical averages to retrieve values with the same unit of measurement, but as these indices are already indexed this strategy would be highly questionable.

A potential drought index insurance scheme would have to account for these index features, set actuarial rates accordingly, and adjust their calculation strategies to result in sound indemnification patterns. However, the purpose of this study is not to create a fully functional drought insurance program, it is to compare the general behavior of drought indices to that of the rainfall index in the PRF. Even if it was within the scope of this project to generate such a system, the resulting payout distributions would no longer be directly comparable to the rainfall index. It is important not to alter the indices too heavily; doing so would risk losing the features of a drought index that make it desirable. However, without making some changes the comparison would not be possible. Accordingly, any adjustment made to the PRF structure in order to accommodate the various indices needed to be minimal, general, and simple. Only two additional aspects were ultimately changed, as described below, leaving the bulk of the PRF structure intact.

Strike Levels

Several strategies to obtain reasonable strike values for the drought indices were explored. One was to simply use the pre-existing drought severity category cutoffs that were chosen by each index's respective author. For the Palmer Drought Severity Index, Wayne Palmer chose 5 categories

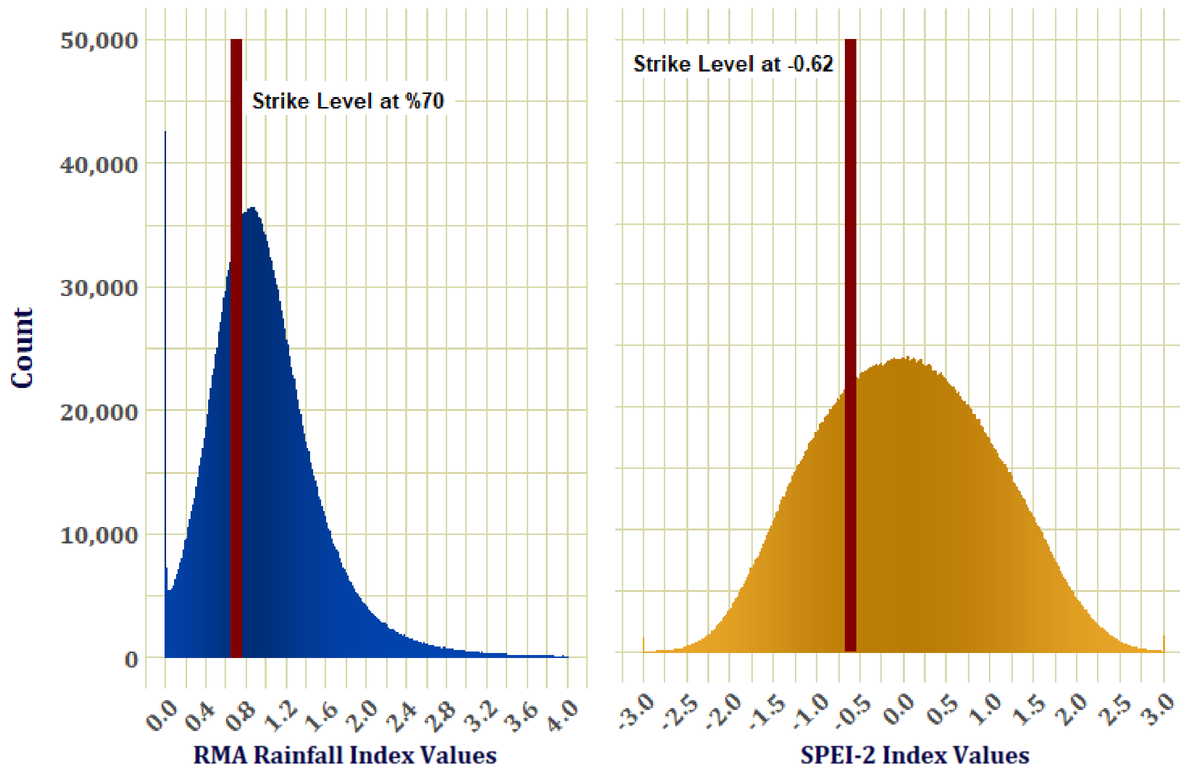

Figure 13. *An example drought index, the 2-month SPEI, with outliers assigned to 3 standard deviations on either side of the mean and an analogous 70% strike set at -0.62. It is compared to the 70% strike level of the unaltered rainfall index.*

of drought ranging from "Incipient Drought" for values between -0.5 and -0.99 to "Extreme Drought" for values below -4.0. Thus, for the PDSI, the first strategy was to set the 90% strike level as associated with incipient drought, the 70% strike level with extreme drought, and insurance payouts were triggered by the PDSI values themselves. Payment calculation factors were generated using these levels as well, but all other calculations were based on the associated strike levels. The original SPI drought severity categories were originally separated into only 4 categories, though 5 categorical cutoffs are often used today. Like Palmer's indices, these generally range from between -0.5 and -.99 for mild drought, but the most extreme category is usually considered to be open-ended and less than -2.0. The same categorical values apply to the SPEI, which was designed around the SPI. Testing showed that these original drought categories are not at all analogous to the strike levels used in the PRF. While middle and high categorical cutoffs triggered payouts at a somewhat reasonable rate, the frequency of payouts at lower strike levels was simply too small compared with the goals and actual performance of the PRF, with many grid cells going as long as a decade between payments. To account for this discrepancy a second strategy was employed and strike levels were set at values with equal probability of occurrence to those of the rainfall index, using the baseline range since 1948. For example, the overall probability of experiencing a rainfall-based payout at a %70 strike level is the same as that of receiving a 6-month SPEI-based payout at a value of -0.54. However, it was also necessary to standardize each drought index to a common scale to make comparison possible and avoid negative numbers. Each drought index was therefore standardized to a scale from 0 to 1 and the strike value in the example becomes 0.41 from a distribution centered on a mean of 0.50. This was done for each index and bi-monthly interval. While these values may not correspond exactly with the drought severity categories imagined by the climatologists who designed them, this step allows the drought indices to function in the structure of the PRF. The rainfall index was not standardized in the final analysis in order to maintain realistic payout results and aid in interpretability of the results. However, a problem of scale remained so one more adjustment was needed.

Payment Scaling

Potential payments generated using the above strategy were consistently smaller than those generated by the rainfall index. National average dollar amounts were between 13.6 and 43.5% smaller depending mostly on the index, though there were some differences between strikes levels. Within each index the ratios were very similar, though the two PDSIs do show significantly higher ratios at the two highest strike levels while the SPEI ratios diminish linearly from low to high levels. Ratios between strike levels for the Z Index and the SPIs are nearly the same.

As mentioned before, these differences would need to be adjusted in an actuarial system designed specifically for each index. To account for this discrepancy and improve the interpretability of comparisons between payouts, a scalar term unique to each index was added to the indemnity calculation in an effort to imitate the effect of a more specified actuarial system. This needed to be done in a general way in order to preserve the inherent structure of each index, but because of the difference in payment ratios between strike levels a simple total ratio could not be used. Therefore, a two-step process was applied to account for both strike level discrepancies and total payout potential. The first step was to calculate the average ratio value between all strike levels of the rainfall index and each alternative index. For each drought index this first scalar became the average of the 5 ratios between payouts from the rainfall index and those of its own at each strike level. Having accounted for the strike level discrepancy, the second scalar accounts for the difference between total potential payouts. The final scalar becomes the product of the first two and the indemnity becomes the product of the PCF, total protection, and this final scalar:

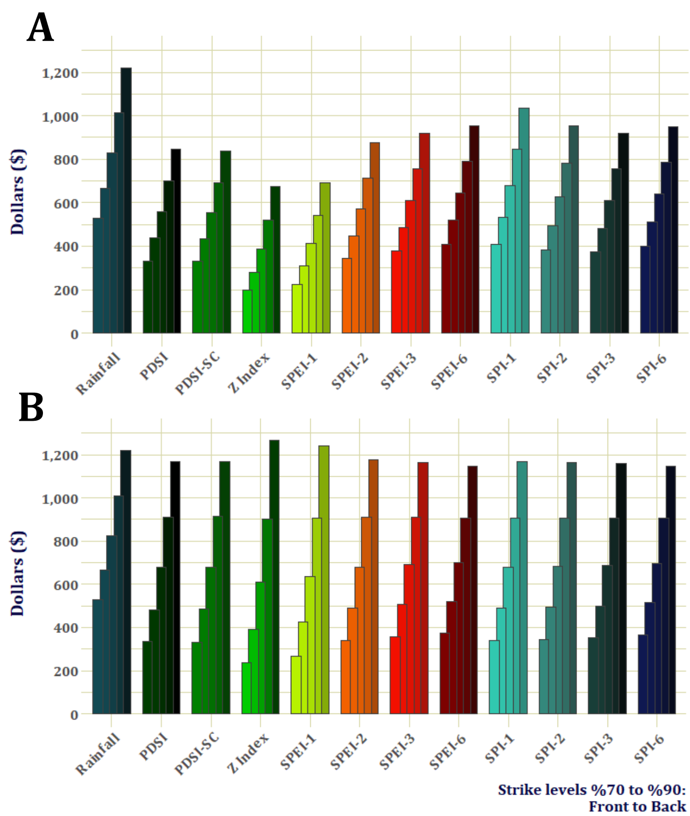

Figure 14. *(A) Nation-wide average PRF payouts resulting from the use of unscaled drought indices. (B) Nation-wide average PRF payouts from drought indices after individual payouts are scaled to match those that result from the rainfall index.*

$$Scalar_1 = 1/n \sum_{\text{strike}=1}^{\text{n}=5} \frac{rainfall\ index\ payout_{strike}}{drought\ index\ payout_{strike}}$$

$$Scalar_2 = \frac{1/n \sum_{\text{strike}=1}^{\text{n}=5} drought\ rainfall\ index\ payout_{strike}}{1/n \sum_{\text{strike}=1}^{\text{n}=5} drought\ index\ payout_{strike} * Scalar_1}$$

$$Scalar_3 = Scalar_1 * Scalar_2$$

$$Indemnity = Payment\ Calculation\ Factor * Protection * Scalar_3$$

The adjusted nation-wide average payment potentials are compared to the original potentials and are displayed in Figure 17. The resulting scaled overall mean payout potentials of each drought index (across all strike levels) is 98% of that for the rainfall index. However, the Z Index and the SPEI-1 exhibit persistently large spreads between higher and lower strike levels. The Z Index exhibits more of this pattern with payout potentials that range from 112% of those from the rainfall index at the 90% strike level to 75.5% of those from the rainfall index at the 70% strike level, while potential payouts at the 80% level were roughly the same at an average of around $800. Excepting these two indices the resulting payments range from 101.4% of the rainfall index for the SPEI-2 at a 90% strike level to 91.2% of the rainfall index for the PDSI at a 70% strike level. When this payment scaling step is combined with the strike level matching step, the resulting payouts are derived with similar chances of occurrence and have very similar average values, leaving features such as seasonality and variance free to vary within similar budgets.

Temporal Basis Risk Assessment

Because weather-based index insurance is not based on any on-site measurement of loss, and rainfall in particular is relatively volatile, there is an element of chance involved with the reception of PRF payouts following drought-induced losses. Also, while cumulative rainfall is extremely important to rangeland health, it is not enough to fully indicate rangeland conditions. A single heavy thunderstorm early in an otherwise dry coverage interval, for instance, may flood the range for a short time and then prevent indemnification from subsequent desiccation. As described earlier, according to PRF rules policyholders cannot insure their range for the entire year, but must split their protection over a limited number of insurance periods, further decreasing the chance of capturing a drought event.

The exact feature of a weather-based index that generates payouts also generates uncertainty for the policyholder, and that is variability. The rainfall index indemnifies more frequently when there is a high level of variance in bi-monthly rainfall. An arid area that experiences generally low precipitation is not more likely to receive a payout than a humid area, unless the bi-monthly level of precipitation more frequently dips far enough below that area's long-term average. Though the RMA advises that the insurance plan works best for the policyholder if they choose to insure the most important growing season months, there are genuine financial incentives not to do so. The chances of receiving a payout increase by selecting whichever months have the most variance in rainfall, regardless of their importance to forage production, and many locations exhibit a distinct set of months that are more likely to pay over time. This pattern might be exploited by policyholders with long-enough local climate records or a good sense of seasonal rainfall patterns in order to maximize profits rather than to genuinely reduce production risks. It might also be a necessary strategy for policyholders who operate in locations with particularly low growing season rainfall variability and who are unable to afford both the insurance premiums and an elevated risk of non-payment after drought. A simple rainfall record can reveal when payouts would have been triggered. It is also possible to calculate bi-monthly payment calculation factors to use as a general estimate of payout magnitudes and trigger frequency to determine the months in which to place a policy's protection for more frequent and/or larger indemnifications.

To illustrate this effect of seasonal patterns in the rainfall index values, several potential payment maps were generated for pairs of seasonal intervals and compared with a payout map generated with an "optimal" interval selection strategy. The maps show the average potential payment for each grid cell between 2000 and 2016 using a hypothetical 50% allocation of coverage for each interval of a 500-acre ranch for the middle (80%) strike level. The first four maps show the results of splitting protection between two intervals in each season. Intervals 11 and 1, or November-December and January-February, were chosen for winter, however this is the only time that consecutive intervals may be selected since these months do not overlap. Intervals 2 and 4 were selected for the spring, 5 and 7 for the summer, and 8 and 10 for the fall. For the fifth map, potential payments for each grid cell were calculated from the two intervals with the highest average payment calculation factor since 1948. National average bi-monthly payments and maximum individual payments are included in each map to indicate broad seasonal differences in payouts and illustrate the potential for payment spikes using each of the 5 strategies. This set of payout maps is then compared to another set that results from a sample drought index to compare differences in seasonality and distribution (Figure 18).

To paint a fuller picture of the seasonal incentive structures for each index on a national scale, maps of the highest PCF intervals are displayed in Figure 19 along with the percentage of area in the spring and summer intervals (3 through 7) for each. These maps do not incorporate any of the county base or premium rates, but instead represent the underlying patterns of payout potential for each drought index.

The analyses above do not incorporate the effect of the strike level which has a heavy influence on payouts. So, in order to more completely compare the potential for temporal basis risk of the program as a whole, the potential seasonal payments from each index at each strike level were collected and are summarized in Figure 20.

Finally, to illustrate the differences in resulting payout patterns between the rainfall index and a sample drought index on a local scale, the same four sample locations chosen for the market analysis are isolated. These locations are the Billings Livestock Commission in Billings, Montana, the Coleman Livestock Auction in Coleman, Texas, the Huss Livestock Market LLC in Kearney, Nebraska, and the Oklahoma National Stockyards in Oklahoma City, and they correspond to PRF grid IDs 30986, 14223, 24724, and 18430. For each a time series of indemnities along with monthly payout trends are generated to illustrate differences in the timing of payments, with special attention given to the national-scale drought of the 2011-2013 period. The same hypothetical policy is used for each location; 500 acres at an 80% strike level between the years 2000 and 2016. These results are displayed in Figure 21.

Results

Seasonality

Seasonal patterns of PCF bias for the rainfall index are very clear and clustered in large regional groups, as is illustrated by the map of the highest average PCF intervals in the bottom right corner of Figure 19. The Central states and peninsular Florida both show a clear bias for the November to December interval, while virtually all of the rest of the East is grouped in one of the two preceding fall intervals. Variance in the Northwest is distinctly highest in the July-August interval while the June-July interval dominates the Southwest. Optimal strategy payments in the southwest would likely be much higher if the RMA had not recognized this trend and removed that season's availability. In other parts of the country, clusters of high optimal strategy-based payments mirror those of the monthly PCF biases, with large groups in the northwest, southeast and central regions. On a national scale, this optimal strategy results in, by far, the highest potential payments with an average of $2,315. The winter season interval selection results in the second highest at $918, and the fall has the third highest with $837. The spring and summer month combinations, generally associated with the grassland growing season, resulted in the least potential payments with average values of about $795 and $770, respectively. Maximum individual payouts had the opposite seasonal pattern.

According to the market analysis, the drought indices and the rainfall index explained very similar amounts of variance in Central US cattle weights, with fixed-effects model R^2 values of roughly 0.79, and, when outliers were accounted for, very similar standard errors and residual distributions. In the absence of conclusive evidence that drought indices better indicate production risks in the

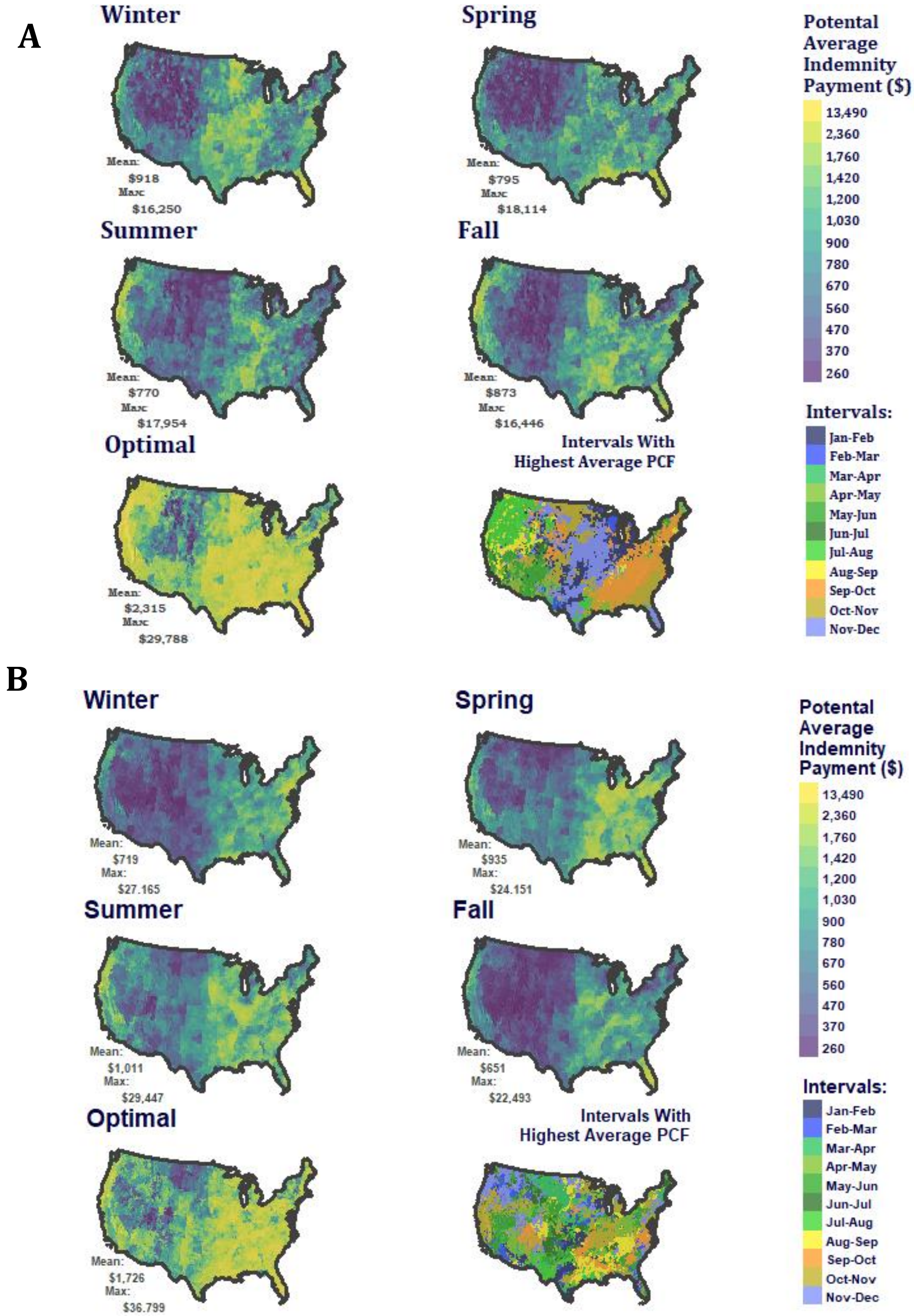

Figure 15. *Maximums, national means, and distributions of potential PRF net payments for policies at an 80% strike level with protection split between pairs of winter, spring, summer, and fall insurance intervals, and with protection split between whichever two intervals had the largest average payment calculation factors since 1948 for (A) The NOAA-based rainfall index and (B) the One-month Standardized Precipitation-Evapotranspiration Index.*

cattle market, the 1-month SPEI was used to illustrate the difference in seasonality between a drought index and the rainfall index. This index was chosen for several reasons: it has the same one-month time-scale as the rainfall index, it incorporates temperature, and at 42.24% it incentivizes a relatively large portion of the US to place coverage in spring or summer months as is illustrated in Figure 20. These maps show that all drought indices have much larger extents of growing season PCF bias, comprising 37 to 44% of the area of CONUS compared to only 28% for the rainfall index. This is true at all strike levels with the highest values occurring at the 70% strike level, and little difference between 80% and 90% strike levels. While the Palmer Indices, and particularly the self-calibrated

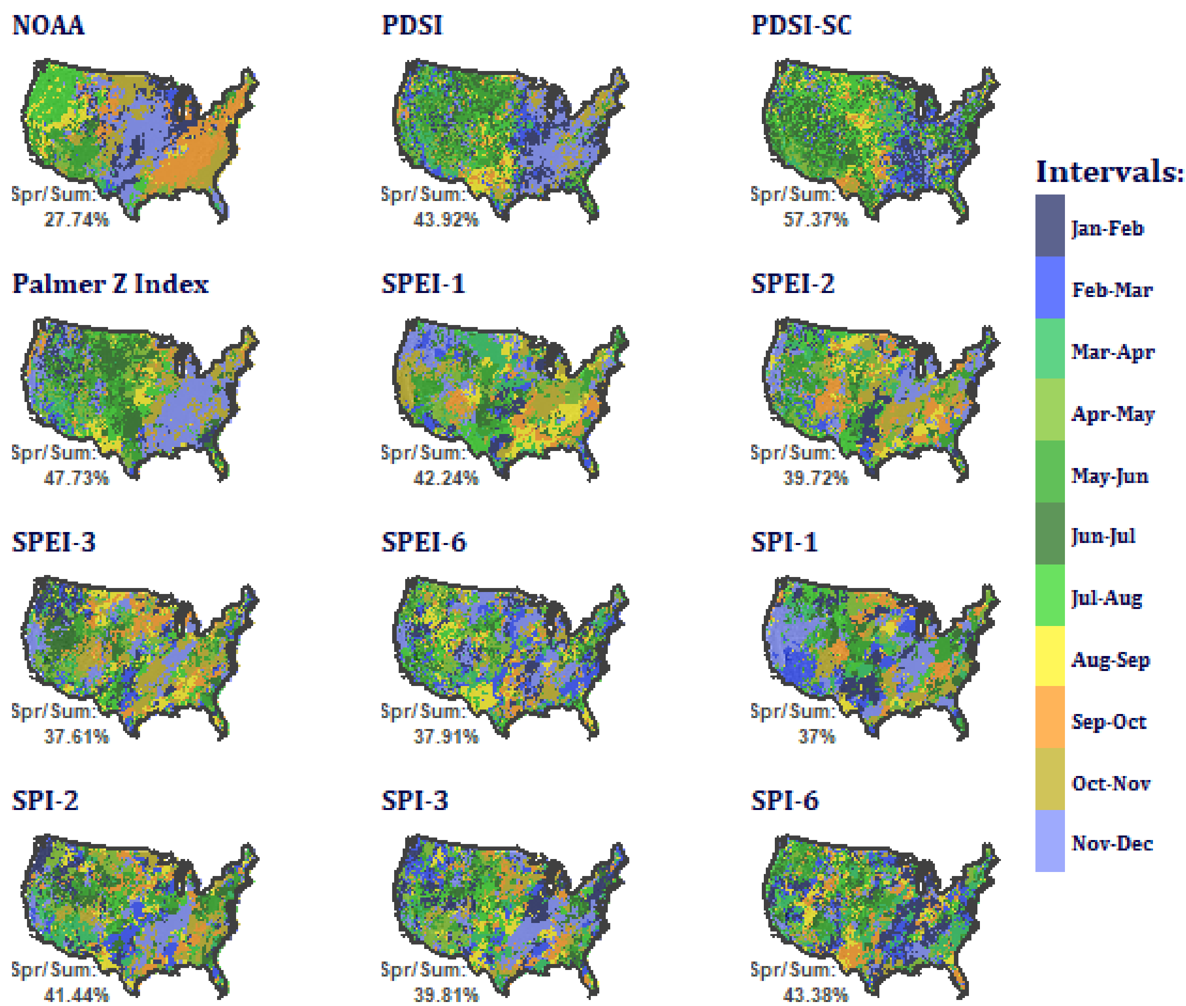

Figure 16. *PRF Insurance intervals with the highest average PCF values at the 80% strike level since 1948, along with percentage of total area in the spring and summer intervals (3 through 7).*

PDSI, have spring and summer bias over the largest portions of the US as a whole, these also have a distinct east-west pattern that would incentivize winter protection over the majority of the east. The 6-month SPI has a larger growing season PCF bias at the 80% strike level, but this is not as consistent across all strike levels as the 1-month SPEI.

When the above process is applied to this index, the seasonality pattern is reversed. After the optimal strategy, the highest paying seasonal combination is summer with an average of $1,011 while the spring intervals were second at $935. The fall resulted in the lowest potential average payout at $651 and the winter resulted in the second lowest at $719. The optimal interval strategy still resulted in considerably higher payout potentials and resulted in a higher maximum individual payout than that based on the rainfall index at $36,799, but the average value was almost $600 smaller at $1,726. This indicates that the disincentive to insure growing season months would be largely avoided using the SPEI-1, while the ability to optimize payouts would be significantly undermined as well.

Every drought index pays more at higher levels than

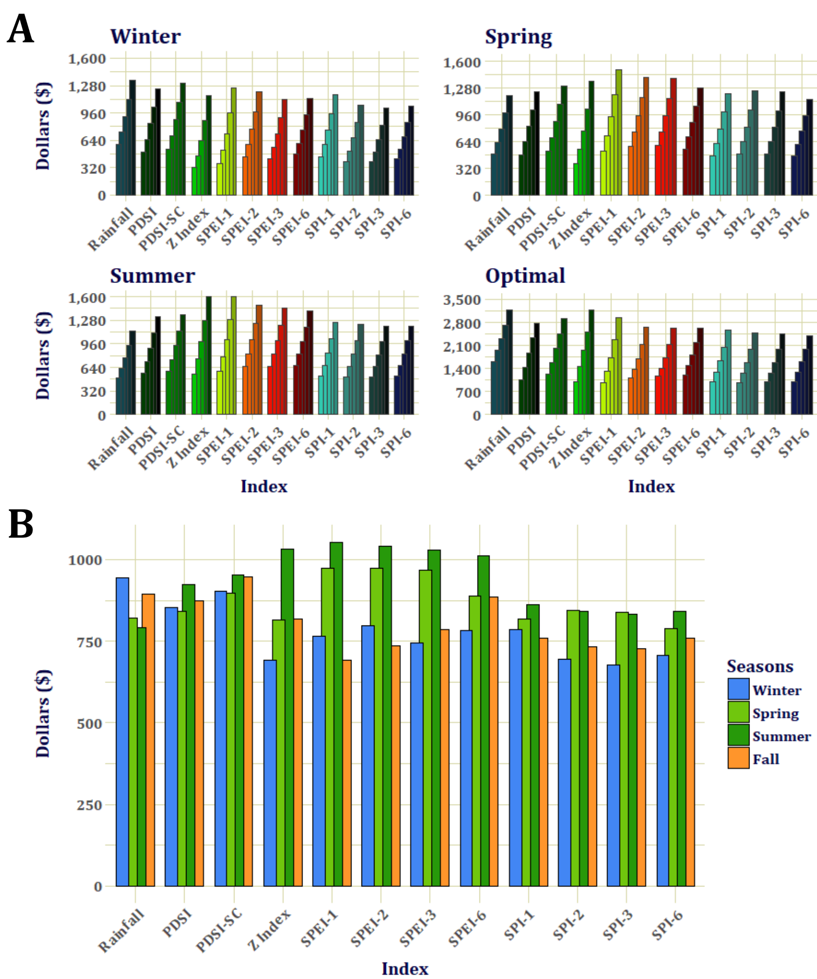

Figure 17. *(A) Potential PRF payouts from each index at each strike level for the winter, spring, summer, and optimal interval allocation strategies. (B) Potential Payouts from each index for each of the seasonal strategies averaged across all strike levels.*

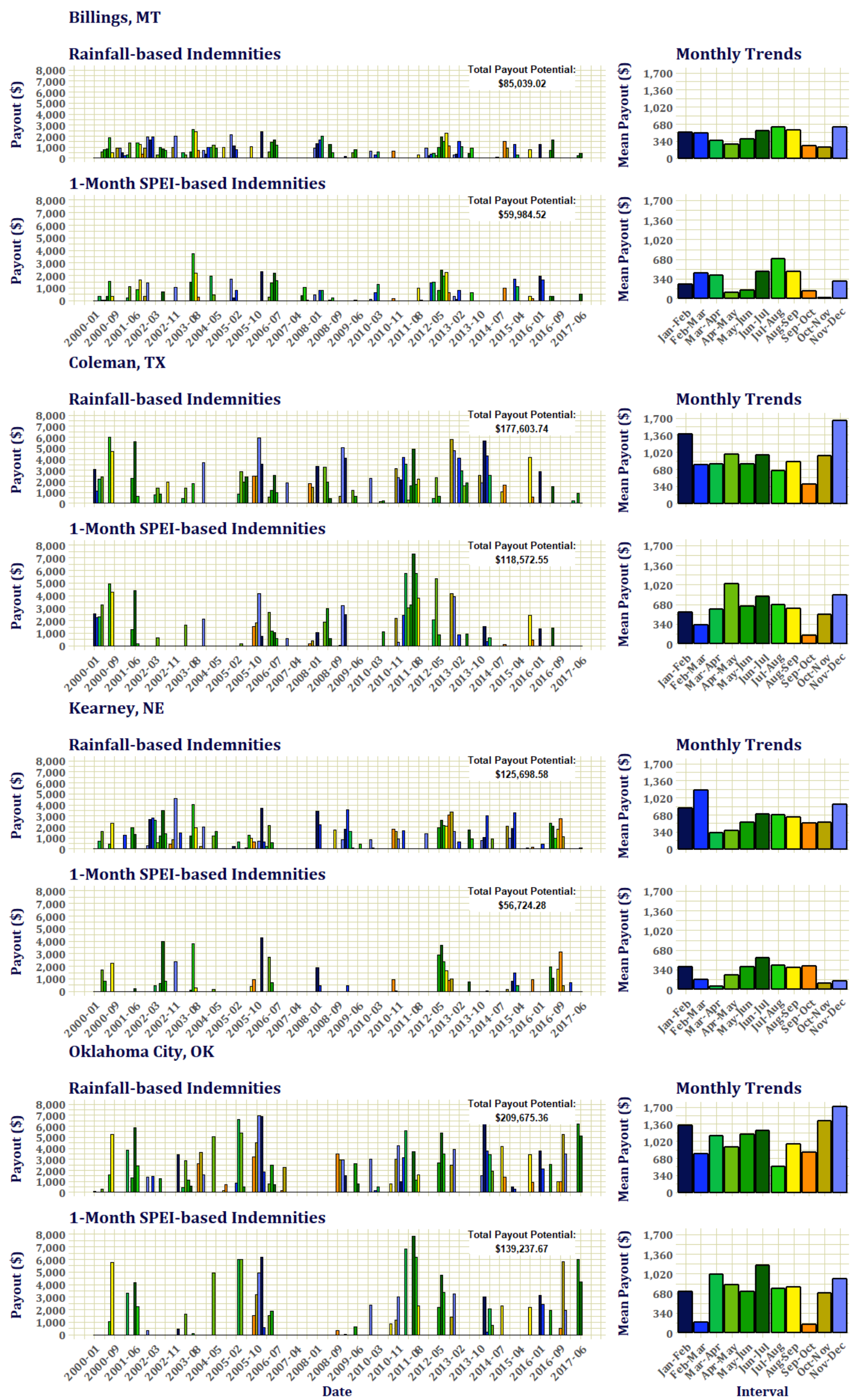

Figure 18. *Time-series of potential payouts at sample locations from the PRF based on the Rainfall Index and the 1-month Standardized Precipitation-Evapotranspiration Index with a policy for a 500-acre ranch set at an 80% strike level and 50% protection allocation for each interval.*

at lower ones. Payouts from the PCF-optimal interval selection strategy are significantly diminished for most of the drought indices, excepting the Z Index at the highest strike levels. The Z Index at 90% actually results in a slightly higher average net potential payout at $3,187 compared to $3,167 for the rainfall index. Maximum individual payments, however, are almost always higher from the drought indices, except for some cases at lower strike levels. The Z Index in particular results in very low payouts at the lower strike levels, except in the summer. When the strike values are averaged into seasonal mean net payouts, the SPEIs show the highest growing season payout bias, with the SPEI-1 at the 90% strike level showing the most at $1,598 and $1,499 for the summer and spring intervals respectively.

The rainfall-based trends generated from the four individual locations reflect the national trends observed above; only in Billings, MT do the highest payouts fall in non-winter months. In Kearney the February-March interval has significantly higher payout potential followed by the prior two intervals, and the November-December intervals pay most at both Oklahoma City and Coleman. None of the winter months have the highest payout potential for SPEI-based policies. The top-paying intervals are July-August for Billings, April-May for Kearney and Coleman, and June-July for Oklahoma. The growing season bias is not perfect and there is considerable variation in the monthly pattern, but in every case the SPEI does incentivize the spring or summer months, while the rainfall-index incentivizes the winter in 3 out of 4 cases.

Payment Consistency

Both the rainfall index and SPEI result in considerably smaller payouts in Billings than in any of the other three locations. Here, there is a clear clustering of relatively large potential payouts in the 2012 period from both indices, though the SPEI results in somewhat higher payments. The rainfall index would have paid in almost every period between mid-2000 and the beginning of 2005. In Coleman, TX, the patterns of payout are very similar, though the rainfall index triggered significant payouts in early 2014 that the SPEI completely missed. The 2012 drought was detected by both indices, but the SPEI payouts during this period were considerably larger. In Kearney, NE the SPEI triggers very few payments and shows the biggest difference in payout patterns relative to the rainfall index while the two indices show very similar patterns in Oklahoma. In all cases the rainfall index pays much more frequently and results in a much larger overall payout potential. The rainfall payout pattern is marked by frequent, small payouts, often in the winter and fall, where there are payout gaps with the SPEI. In most cases the 2011-2013 period resulted in larger magnitude payouts for the SPEI, though both indices detected this period similarly well.

The resulting time-series of payouts from the longer-term drought indices show a different pattern. Generally, the longer the time-scale of the index the more grouped the payouts become, with very consistent payout potential during droughts and few in between. While there may be some aversion to the use of long-term indices as discussed in the Z Index description (chapter 2), this would be a desirable trait in that a policyholder would be very unlikely to miss a payment during drought while policy providers would be much less likely to have to pay when there is none.

Consider the case of the self-calibrated PDSI (PDSI-SC) in Coleman, which is in central Texas, where major droughts were experienced in the years 1999-2000, 2005-06, 2008-09, 2010-11, and to a somewhat lesser degree in the several following years as the 2011 drought expanded northward (Nielsen-Gammon, 2011; USDM, 2018). The resulting payout distributions from this index are displayed in Figure 23. The PDSI, according to Guttman (1998), has an autoregressive influence of 2-9 months depending on the location. While the total payout potential from the PDSI-SC and the rainfall index is almost the same at about $179,000 and $176,000 respectively, the PDSI-SC pays out during every interval within the drought periods and for only one interval in between. With the gaps in payouts present in the rainfall index and any of the shorter-term indices it would have been possible for a protected rancher to, by chance, choose the wrong intervals and receive little

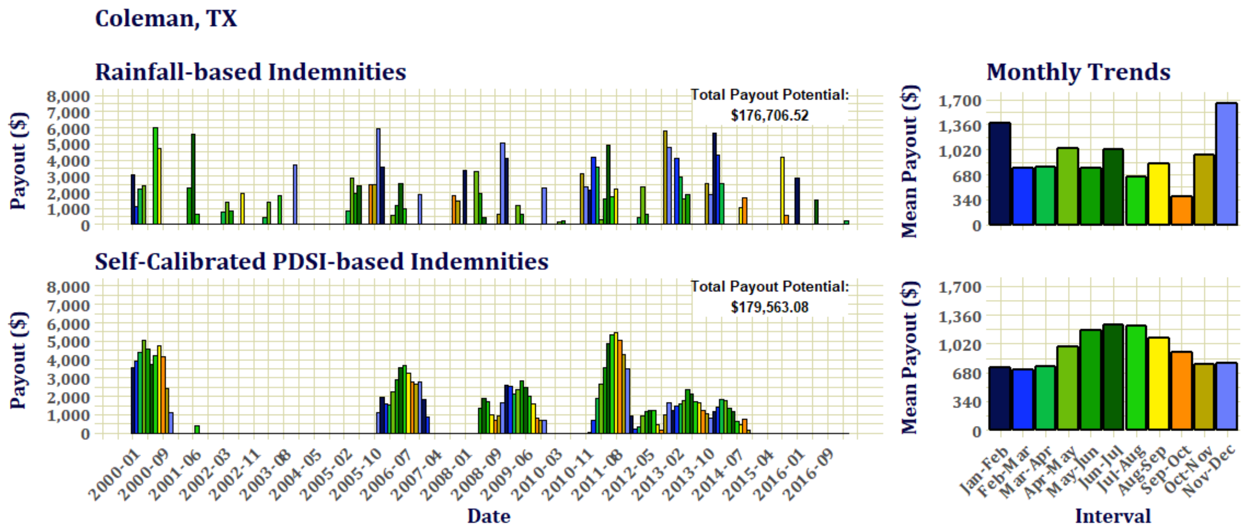

Figure 19. *Time-series of potential payouts at a grid cell in Coleman, TX from the PRF based on the Rainfall Index and the Self-Calibrated Palmer Drought Severity Index with a policy for a 500-acre ranch set at an 80% strike level and 50% protection allocation for each interval.*

compensation from these droughts. If they used a consistent strategy and chose to follow the advice of the RMA by insuring growing season months, intervals 5 and 7 for example, they would have received $6,070 from the rainfall index compared to $15,357 from the PDSI-sc throughout the 2010-2013 period of southern US drought. The rainfall-based PRF would have reimbursed this Texas rancher $2,579 for 2008-2009 drought when the PDSI-sc would have triggered $7,884. In Billings, MT, for the drought in 2012 and 2013, a rancher with the same strategy would have received $3,382 with the rainfall index compared to $6,438 from the PDSI-sc.

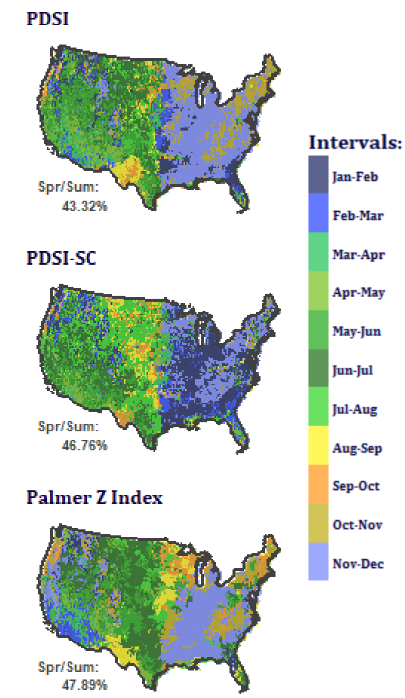

Figure 20. *Maps of Highest PCF Seasonality resulting from the PRF under each of the three Palmer drought indices at the 90% strike level.*

The east-west seasonality boundary exhibited by the Palmer drought indices is particularly distinct at higher strike levels. At the same time, and more so for the PDSI-SC, they tend to encourage growing season protection over the largest portion of the US at medium to low strike levels, and with a very even distribution. Considering these results, it was decided to take a closer look at the PDSI and why it exhibits such a distinct pattern when used as an alternate index in the PRF.

The total value distribution of the PDSI used in this experiment exhibits a distinctly bi-modal distribution of index values, with peaks at around 1.5 above and below zero (Figure 24). This feature is not present in the Z Index, and so probably arises from the autoregressive aspect of the other two that is not shared by the Z Index. However, the split in maximum monthly PCF trends is present in all three indices, so the autoregressive aspect of the PDSI calculation is an unlikely cause. For each, the boundary occurs along the 98^{th} meridian with a very recognizable pattern, one that is unique for its distinctly linear shape and that is almost completely related to rainfall. The "100^{th} parallel"

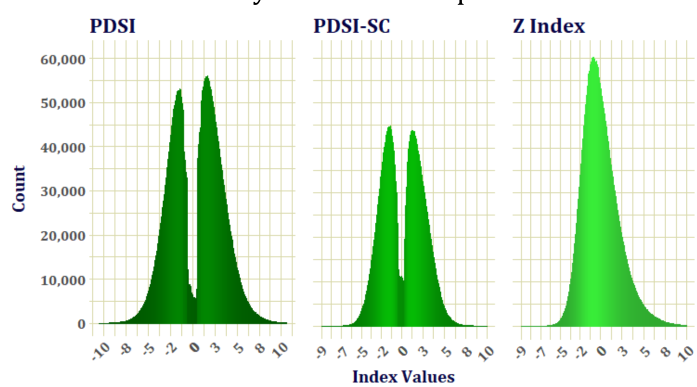

Figure 21. *Value distributions of the PDSI, self-calibrated PDSI, and Palmer Z Index with 1,000 bins across CONUS for the PRF baseline calculation period between 1948 and 2016.*

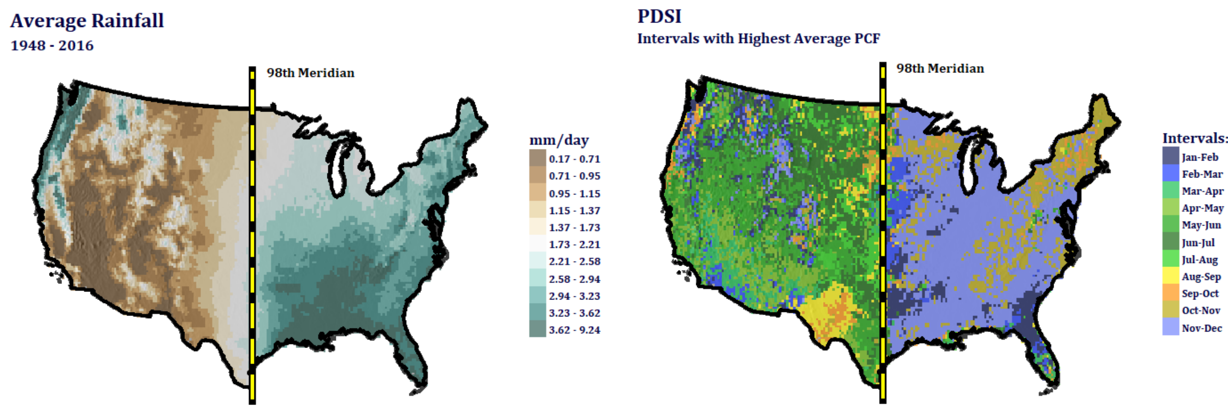

Figure 22. *Patterns of rainfall and PCF seasonality with the PRF under the PDSI along the 98th meridian.*

(more precisely the 98th meridian) represents a genuine and well known climatic distinction between the East and West, famously discovered around 1878 by geologist John Wesley Powell. Generally, areas west of this line experience less than 2 mm of average daily rainfall, while more than 2 mm is experienced east of it. Ironically, 19th century financiers and insurance companies purposefully avoided investing in any potential enterprise or policy west of this line because of the perceived risk. This aversion was so strong that it resulted in distinctly linear social patterns of distribution, such as population density, along the parallel (Leifert, 2018). However, the rainfall pattern is not as linear as this social pattern; the line veers eastward north of Nebraska (Figure 26). The PDSI and the PDSI-SC seasonal PCF trends both look more like these population maps with a completely linear seasonality boundary at the 90% strike level. The Z Index aligns more with the rainfall pattern having maximum PCF intervals that occur in the fall east of the Dakotas and into Minnesota, though the summer boundary remains.

Why this particular pattern arises in the Palmers and not the other drought indices is unclear. Even the rainfall pattern does not fully explain the straight boundary of seasonality because of the deviation in the north, even though it was in rainfall that the 98th meridian phenomenon was originally discovered. It would seem reasonable to connect the observed bimodal index value distributions with this distinct seasonal pattern of PCF magnitude, but the Z Index does not exhibit a bimodal distribution despite exhibiting the same pattern. However, a pattern of vegetation may exist that does correspond well.

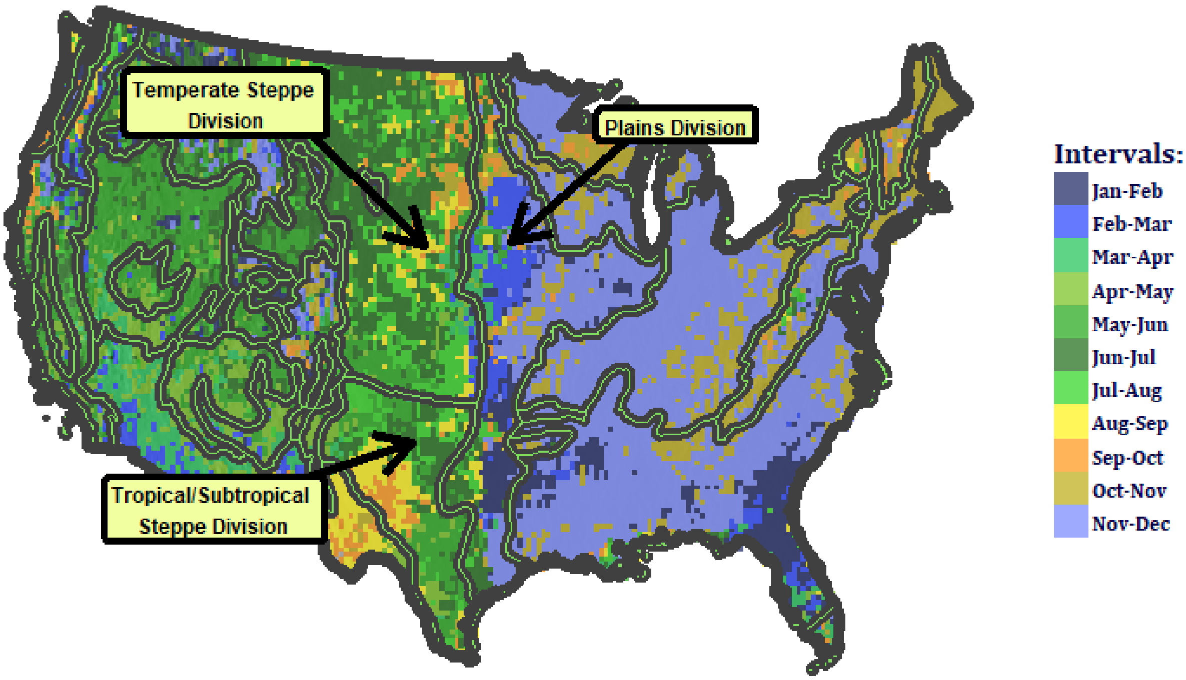

Figure 23. *Patterns of PCF seasonality under the PDSI and US Forest Service Ecoregion Divisions.*

Consider the concept of an ecoregion: an area in which climate patterns and ecosystem compositions are relatively similar within itself, and distinct from other areas. Of the several delineations of ecoregions that are used by different US agencies, the one used by the US Forest Service provides a linear pattern that corresponds with fairly high precision to that of the seasonality exhibited in the Palmer drought indices (Figure 26). This product was created as a map in 1976 by Robert G. Bailey while working for the Forest Service and delineates ecoregions at various scales called Domains, Divisions, Provinces, and Sections in order of decreasing size (Bailey, 1976). According to the map, in the northern portion of the US, there is a linear boundary between the Temperate Steppe division on the west side, where water loss to evaporation is typically higher than replacement by precipitation and which is characterized by short-grasses and shrubs, and the Prairie Division which is dominated by tall grasses and broad-leaf herbs on the east side where the balance between precipitation and rainfall is roughly equal. In the South the boundary is between the Prairie Division on the east side and the Tropical/Subtropical Steppe Division which is dominated by short-grass species and where evapotranspiration exceeds precipitation (Bailey, 1983). More broadly, this line divides the Humid Temperate Domain that dominates the East from the Dry Domain that extends nearly all the way to the west coast.

Whether the seasonality detected in the indices also causes the vegetative differences, or the vegetation itself affects the ET calculation of the indices, the patterns are clearly related. Considering the ecoregion descriptions above it seems most likely that vegetation and the Palmer indices are both responding to distinct differences in the balance between evapotranspiration and precipitation. This indicates that the Palmer indices are likely capable of distinguishing between impacts of drought in different rangeland ecosystems and, as such, are likely able to indicate impacts to rangelands in particular.

Discussion

The comparison of the PRF with the self-calibrated PDSI and the rainfall index in Coleman, TX is illustrative of the risk involved with an insurance plan based on a rainfall index, and of the potential improvements that could be made by using a drought index in its place. In the case of the current PRF, a rainfall index can provide adequate protection through a drought if the right insurance intervals are chosen, but it would be very easy to choose low-paying intervals or miss needed payments altogether. This might be compensated with frequent smaller payments over time, though reception of these could also be easily missed. The PRF under the longer-term drought indices, in contrast, is very resilient against missed payouts during droughts and does not tend to pay at all during drought-free periods.

The results of these experiments also highlight a general incentive under the rainfall index to strategize and insure the months with the highest chance of payout, and this incentive undermines the specificity required for an effective index-insurance plan. In fact, the least important months to forage growth are often those that are most incentivized under the PRF rainfall index. While the information on the timing of potential payouts may not be directly available to policyholders, for any single location it would not be too difficult to calculate historical payout frequencies or payment calculation factors to determine which insurance intervals are likely to payout the most, whether or not those intervals fall in the critical forage growing seasons. Ranchers are also more likely to be able to estimate these trends than the average citizen because their livelihood depends on the weather.

It has been demonstrated that this incentive can be largely ameliorated by substituting the rainfall index with a drought index using only a few simple adjustments. Each of the drought indices that were used in this experiment showed a growing season biased average payment potential, and most also showed a lessened potential for profitable strategic interval selection. This means that, without having to make difficult coverage restriction decisions or use a complicated methodology like the growing degree day strategy of Conradt et al (2015) to select the most appropriate interval availability windows by grassland type, the simple nature of these drought indices would largely account for temporal basis risk by means of incentivization.

Challenges

There would be challenges involved with the use of a drought index. First, a tight fit of index values around their means can result in relatively fewer payment triggers at lower strike levels than the rainfall index in some parts of the country, despite accounting for the issue on a national level. Research does suggest, however, that this situation might actually be a boon for the long-term viability of the industry. Müller et al (2011), studying rangeland management behaviors with an economic model calibrated to livestock producers in Namibia, find that rainfall-index based plans which result in a high frequency of payout triggers can incentivize riskier rangeland management, leading to a more rapid degradation of rangelands. They also find that less frequent payouts at lower strike levels do not incentivize unsustainable practices while still improving the economic well-being of the producer. Specifically, they find that payout frequencies resulting from a strike level of 75% of normal rainfall is optimal for this latter condition.

Whether these findings apply to American ranchers is uncertain, but the same principles of management apply; namely, whether or not the manager chooses to allow a portion of the land to rest during wet years while adjusting stocking rates to account for reduced carrying capacities during dry years. According to Müller et al's model, managers without insurance who utilize relatively conservative stocking rates during wet years are not able to maximize their revenues for these years, but do maintain more consistent income in the long run, and that serves as a form of "natural insurance". This certainly applies to American ranchers, especially in the arid to semi-arid West, where it is necessary to consider the ecological resilience of the range to inevitable drought.

While the SPEI-1 fits the conditions above by triggering a relatively small number of payouts even at the simulated 80% strike level in the Central US, it demonstrates that there can be significant gaps between payouts during drought periods when using a short-term drought index. This quality lends further support to the use of drought indices with longer time-scales which would be well justified because drought is a distinctly multi-month phenomenon. Regardless of whether a one-month drought index is more suited to the detection of one-month impacts than the rainfall index, it may be inefficient to insure against short-term impacts altogether. Even when these one-month metrics are averaged across two months, they show an inconsistency that leaves a portion of payout probability up to chance.

The longer-term indices better account for this inconsistency and show a high degree of certainty in payouts during drought periods with a concomitant certainty of non-payouts during non-drought periods (this is demonstrated in Appendix B & C using the PDSI-SC and 6-month SPI). Any monthly time-scale can be selected for the SPI or SPEI, though only the 1-, 2-, 3- and 6-month scales are represented in this experiment. This allows for a high degree of flexibility and ease of calibration when selecting the optimal index. The length of the indices' "drought memories", though, might create some potential for adverse selection. The choice of which intervals to protect in the PRF must be made by the November prior to a policy's insurance year, which means that a known drought in late fall or early winter could encourage policyholders to select late winter or early spring intervals of the following year, knowing they have a higher chance of payout. Therefore, it might be most appropriate to compromise and use a 2- or 3-month index which would provide some of that certainty while avoiding the potential for adverse selection during the sign-up period. At three-months, any known drought conditions leading up to November will have minimal influence on the initial January-February interval of the next year, and at 2-months it would not be an issue at all because there is no overlap between December and January. Of course, it would also be simple enough to move the sign-up period to an earlier month (as Luo et al (1994) suggested for weather forecasting and the MPCI) and maintain the certainty involved with a 4-month or longer-term indices.

Just as with the rainfall index, the performance of a drought index will vary significantly by region according to the criteria examined in this experiment. The most appropriate index for the nation as a whole will exhibit nation-wide payment trends that are most biased towards higher indemnification in the spring and summer months, that is resilient against optimal interval selection strategies, and that creates protection certainty on the part of the policyholder. While the Palmer Drought indices would incentivize growing season protection for the largest portion of the Contiguous US as a whole, this latter feature is only true for the West; at higher strike levels they actually incentivize winter or fall selection over the entire eastern half of the country.

Also, while it is important to include temperature in the chosen index to best indicate rangeland damage from drought, this inclusion must be handled with care in a warming climate. Many researchers agree that drought indices which use the Thornthwaite method (TM) of deriving potential evapotranspiration (PET), though tracking more sophisticated climate models well up to the present, may break down under future, higher temperature conditions (Hoerling et al, 2012; Feng, 2017; Dewes et al, 2018). In climate models they consistently predict unusually severe drought conditions which are possible artifacts of the calculation used. The TM method calculates PET using only temperature and latitude as input variables, meaning that any increase in temperature can cause a proportional increase in the severity of drought detected by the indices which use it, even if moderating factors such as cloudiness or relative humidity are present in the environment. Feng (2017) finds that the more complex Penman-Monteith method (PM) corresponds better with the future climate projections of sophisticated land models under warming scenarios in the Great Plains, while Dewes et al (2017) finds that this method results in less severe predictions of drought severity than several other complex methods. It is possible to calculate most of these indices with the PM method and this was demonstrated most recently by Ficklin et al (2017) who managed to do so with the PDSI. However, Hoerling et al (2012), also operating in the Great Plains, claim that the temperature dependency is still too strong with the PM method. This would suggest that if insurers were to use any of the present drought indices with either of the two most popular PET calculation strategies, their utility could eventually weaken in an insurance setting, and perhaps quickly if the more severe temperature projections manifest.

For a drought-index insurance program to work well over time, it ought to take this information into consideration. Hoerling et al (2012) suggest that future drought index algorithms should calculate PET using sophisticated land models that incorporate many additional variables such as plant phenology, canopy cover, and root interactions with groundwater. While data constraints have led to the adoption of less efficient methodologies in the past, it may now, or soon, be possible to implement such strategies in a cost-efficient manner. The problem of calculating appropriate baseline climate averages with which to derive index values may prove troublesome if long-term records of the additional parameters are not available. However, considering that drought indices such as the PDSI were found to have a good track record for the temperature ranges in which they were calibrated, it might be possible to change PET methodology without recalculating baselines.

As with other natural hazard mitigation programs, a weather-based insurance program will need to be flexible enough to consistently adjust as the climate warms. If this proves to be an intractable problem for drought insurance, the Standardized Precipitation Index should be considered because it would be immune to this problem while providing many of the same benefits as the drought indices which include temperature, and this is demonstrated with a panel of potential payout time-series in Appendix C. Though the SPI would encourage significantly less growing season protection than the SPEI, it would still do so to a higher degree than the two PDSIs would for the eastern portion of the US at higher strike levels, and much more so than the rainfall index would across the entire nation for any strike level. The multi-scalar nature of the SPI has also been demonstrated to exhibit a potential for increased certainty of indemnification when compared to the rainfall index.

Palmer Drought Severity Indices

Considering the principles outlined in Smith and Watts (2009), the choice of the most appropriate drought index might depend as much on its familiarity with the ranching community as on any of the benefits performed in this experiment. This is only speculation, and would require more analysis of the perceptions of ranchers, but the attractiveness of an insurance product based on an index that ranchers have used and trusted for years might encourage a level of added participation that could possibly account for minor technical limitations. This may also apply to the amount of premiums ranchers are willing to pay to participate because, as Smith and Watts point out, the risk of non-payment with an index insurance plan will certainly reduce its perceived value to an agricultural producer when compared to a direct loss-based plan.

While the USDM would probably count as the most trusted loss-metric, the technical issues associated with this product described earlier could make it very difficult to implement. The Palmer Drought Severity Index, on the other hand, more than satisfies this condition; given its long-term and sustained popularity it is probably the most familiar product available. Also, the extreme winter PCF bias in the East is only present at higher strike levels. As Müller et al (2011) discovered, index insurance at high-strike levels with high payout frequency can lead to unsustainable management practices that could ultimately undermine the long-term resilience of the system rather than support it. At lower strike levels each of the two Palmer Drought Severity Indices exhibit the largest areas of growing season PCF bias and are very evenly distributed across CONUS (Appendix A). Also, the correspondence of the PCF seasonality patterns with the US Forest Service Ecoregions lends support to a hypothesis that the Palmer products are particularly well-suited as indicators of rangeland health.

These indices demonstrate why the selection of the most appropriate index for insurance is a complex decision. It would not be advisable to use these products as the basis for loss at higher strike levels in the PRF because they would cause geographic inequalities in the program's effectiveness between the East and West. However, if the lessons of Müller et al were taken into account when developing a different drought index-based product for the US that used lower strike levels, the performance of these indices could justify their use. With 60% percent of the contiguous US having maximum PCFs that fall in the growing season at the 70% strike level, the self-calibrated PDSI in particular would lessen temporal basis across the largest portion of the United States.

CHAPTER V

CONCLUSIONS

The availability of the Pasture, Rangeland, and Forage rainfall-based insurance represents a move away from historically reactive drought mitigation strategies for the under-protected ranching community of the United States. By targeting only the costliest natural hazard to ranching and avoiding the issues of moral hazard and adverse selection, it circumvents many of the problems associated with federal multi-peril crop insurance plans that cause apprehension towards state-sponsored risk protection in the livestock production industry. As an insurance plan, it also has the potential to allay much of the costs associated with the inefficiency of frequent disaster relief. However, while the PRF will certainly provide financial support and protection against drought-induced losses associated with rangeland productivity, it remains to be seen whether it will do so effectively, efficiently, and sustainably using the current index as the indication of loss.

An effective index must be highly correlated with the insured item, while an efficient index will exhibit precision and timeliness of indicated losses. Under the current structure of the PRF, it has been demonstrated that the rainfall index incentivizes protection of non-critical seasons to rangeland productivity in much of the country, which could lead to a form of seasonal adverse selection. This incentive undermines the intentions of the Risk Management Agency which advises policyholders to place their protection in growing season months, as well as the specificity required for an index-based insurance plan to function as intended.

It has been demonstrated that a drought index-based variant of the PRF would largely supersede this problem by incentivizing protection in the spring and summer months. While the rainfall index and each of the drought indices tested in this study appear to indicate roughly the same amount of climate-related economic impacts in the cattle ranching industry, each of these drought indices would encourage growing season protection for much of the country. Also, concerns of unreasonable payment patterns, such as massive or overly frequent indemnification, under these hypothetical policies have been demonstrated to be easily avoidable using any of the indices tested here. In fact, for the longer-term drought indices, there would be a level of payment consistency and certainty during drought periods, along with an absence of payment during non-drought periods, which might be desirable for both insurance providers and policyholders. While a short-term drought index would incentivize growing season protection for a much larger portion of the US than a rainfall index, a longer-term drought index would do so while also removing an element of chance associated with short-term indices and significantly minimize the probability of a missed payment during drought.

When considering the nation-wide performance of each index, the Standardized Evapotranspiration-Precipitation drought indices would provide the highest incentive to protect growing season months, but the self-calibrated Palmer Drought Severity index would spread this incentive across the largest portion of the US. Using an autoregressive strategy, they also incorporate the effect of time-scale in their calculation and, while this scale cannot be adjusted, this would also provide similar levels of certainty and consistency as the SPI or SPEI. The Palmer Drought indices are unique in that they clearly indicate the distinct difference in climate and ecosystem type between the East and West along the 98th meridian, possibly indicating a unique ability to detect rangeland-specific drought impacts. Also, the two Palmer Drought Severity products tested here were the only drought indices that detected positive effects of climate variation during the growing season of the second year prior to sale in the market analysis, and this might also indicate a higher ability to capture rangeland impacts.

At higher strike levels, though, the Palmer Drought Severity Indices would generate a distinct incentive to cover winter and fall periods in the east, which would lead a significant geographic inequity in the performance of the insurance program. However, at mid- to low-level strike values, these products would actually generate the most evenly distributed pattern of growing season incentivization across the US. Given research that suggests higher strike levels in weather-based index insurance programs may encourage maladaptive rangeland management practices, it would be worthwhile to consider the possibility of a PDSI- or self-calibrated PDSI-based insurance plan which is restricted to these lower levels. In combination with the features described above, the possibility of higher participation rates that could result from the use of a product as well-known and trusted as the PDSI would also support an examination into utility of this product in an insurance setting.

It is important to note that the products assessed here are but a small subset of the available drought indices that are appropriate for indicating agricultural drought; consider the extensive list outlined in Moorehead et al (2015). Also, the multi-scalar capacity of many newer products would provide a high level of flexibility when choosing the most appropriate index for an insurance plan by allowing the time-scale to be adjusted to desired levels of actuarial performance and impact detection. Given this, the most appropriate product for use in a drought index-based plan might not be present in this subset, but, generally, it has been shown that drought indices do show a high potential to decrease basis risk involved with a weather-based insurance program geared toward the cattle industry in the US. There would be challenges associated with their implementation, but these do not appear to be insurmountable. From a broader perspective, the use of drought index-based insurance to mitigate drought impacts in the cattle ranching community is feasible and would represent a step toward targeted and proactive drought hazard preparedness in the US.

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APPENDIX A

Most of the PRF performance maps displayed above were generated using the middle insurance strike level (80%). There are, however, significantly larger portions of CONUS that would incentivize growing season selection at the lower strike levels, particularly when using the Self Calibrated Palmer Drought Severity Index (PDSI-SC), and so maps of the seasonality of maximum payment calculation factors are included here.

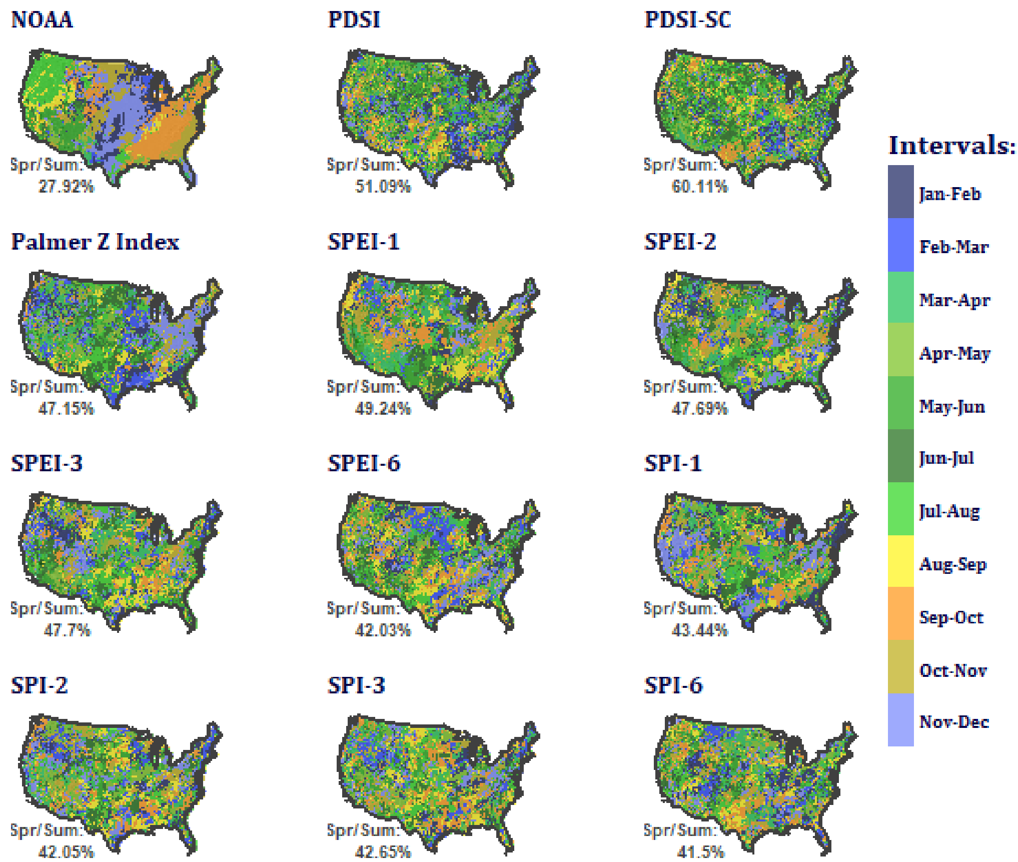

Figure 24. *PRF Insurance intervals with the highest average PCF values at the 70% strike level since 1948, along with the percentage of the total CONUS area in the spring and summer (intervals 3 through*

APPENDIX B

These time series of experimental payouts in four locations show the difference in payout distributions from an insurance plan based on rainfall and one based on the Self-Calibrating PDSI.

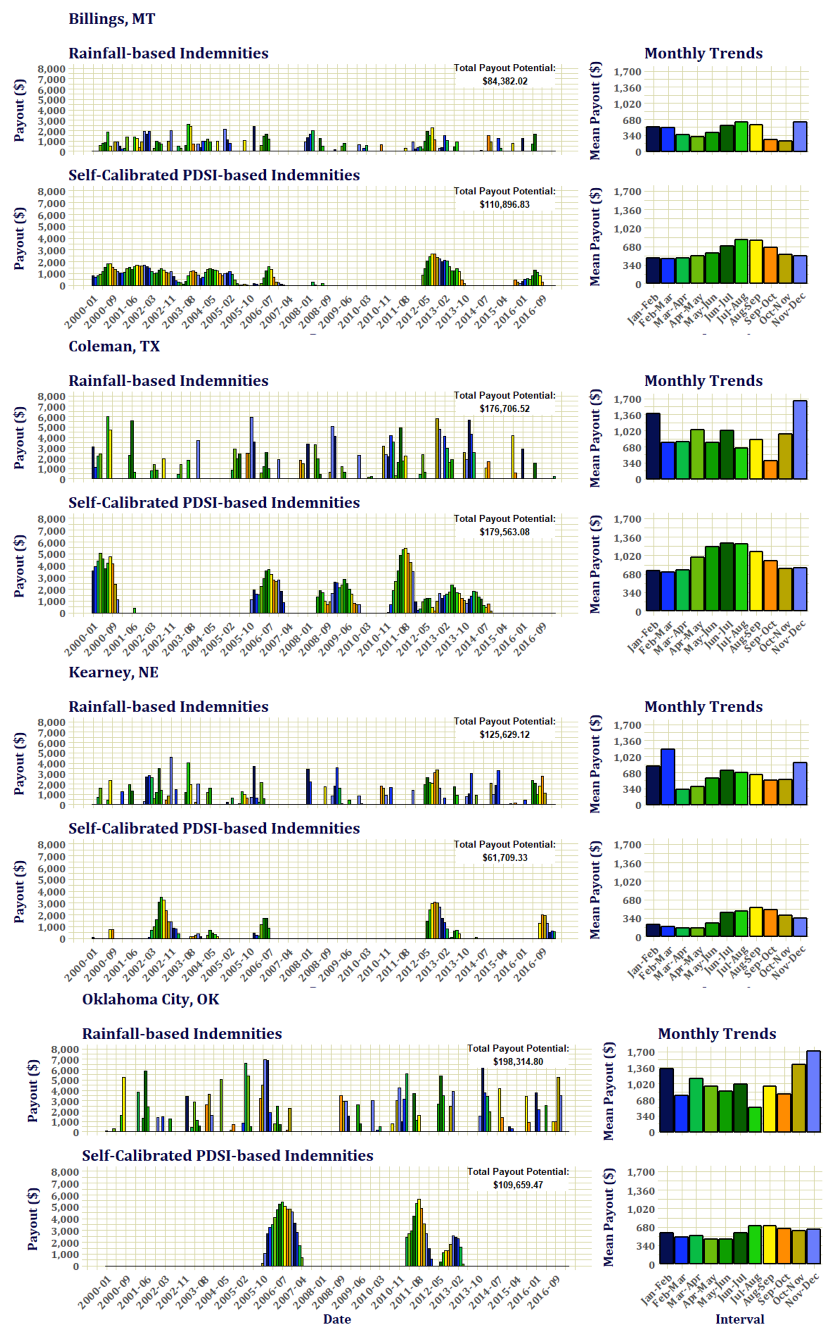

Figure 25. *Time-series of potential payouts at sample locations from the PRF based on the Rainfall Index and the Self-Calibrated Palmer Drought Severity Index with a policy for a 500-acre ranch set at an 80% strike level and 50% protection*

APPENDIX C

These time series of experimental payouts in four locations show the difference in payout distributions from an insurance plan based on rainfall and one based on the 6-month Standardized Precipitation Index.

Figure 26. *Time-series of potential payouts at sample locations from the PRF based on the Rainfall Index and the 6-month Standardized Precipitation Index with a policy for a 500-acre ranch set at an 80% strike level and 50% protection allocation for each interval.*

APPENDIX D

While the fixed-effects panel model results showed that seasonal rainfall or drought index values over the previous two years can explain 79% of the variance in cattle weights at market, they also showed that the same variables can explain about 95% of the variance in price ($/cwt). Just as with the cattle weight predictions, the different drought indices and the rainfall index explain very similar amounts of variance, with similar standard errors and residual structures, though there is little seasonality in price.

500 km Regression Results - Two-Way Fixed Effects

VARIABLES	(1) Rainfall Price	(2) PDSI Price	(3) PDSI-SC Price	(4) Z Index Price	(5) SPI-1 Price	(6) SPI-2 Price	(7) SPI-3 Price	(8) SPI-6 Price	(9) SPEI-1 Price	(10) SPEI-2 Price	(11) SPEI-3 Price	(12) SPEI-6 Price
Constant	79.5592***	79.9589***	77.2525***	72.3433***	74.7801***	76.1952***	79.7837***	79.7380***	74.4631***	76.0839***	79.4304***	79.4163***
Index Values:												
- Month of Sale	2.2209***	3.6848***	6.1176***	2.9836**	3.1028***	3.5734***	3.5962***	3.3097***	3.6237***	3.8181***	3.5199***	3.1210**
	(0.7046)	(1.3258)	(1.8806)	(1.1903)	(1.0423)	(1.1705)	(1.2359)	(1.2359)	(1.0890)	(1.2297)	(1.2343)	(1.1986)
- $Winter_1$	5.2487***	1.1395	-0.6052	8.4782***	9.0288***	5.5662***	7.2598***	-6.2671**	9.6272***	4.8569**	7.0625***	-7.2648***
	(1.4978)	(2.0777)	(3.4249)	(2.8271)	(2.4109)	(1.9721)	(1.8141)	(2.4484)	(2.4667)	(2.0107)	(1.8906)	(2.6646)
- $Spring_1$	2.0249	0.2811	2.4150	3.1788	2.3317	2.8959	1.0956	8.6977***	2.5791	3.1103	0.9943	9.5559***
	(1.6283)	(2.6799)	(4.0773)	(2.1422)	(2.0632)	(1.9247)	(2.0864)	(2.3997)	(2.1590)	(1.9561)	(2.0217)	(2.5864)
- $Summer_1$	-4.3622**	-0.0417	-0.6361	-3.6744*	-4.6457*	-2.7530	-0.7695	-5.5340**	-4.8592**	-2.0093	-0.0295	-5.7573**
	(1.7741)	(2.4537)	(3.4691)	(2.0283)	(2.3787)	(1.8302)	(1.7997)	(2.4154)	(2.2009)	(1.5999)	(1.6651)	(2.5027)
- $Fall_1$	-1.5205	-1.6326	-2.0840	-0.4900	-2.9462	-2.9020	-8.8156***	4.8214	-4.0676	-3.5063	-9.0108***	5.2046*
	(2.1529)	(2.1906)	(3.3274)	(3.1645)	(3.2830)	(2.4213)	(2.8845)	(3.0751)	(3.1779)	(2.3947)	(2.7737)	(2.8616)
- $Winter_2$	4.3648***	4.9331*	4.2718	7.3049**	5.7916**	4.0775**	5.9993***	1.2042	6.0909***	4.1001**	6.4601***	1.8830
	(1.6001)	(2.5090)	(3.9031)	(2.8481)	(2.3967)	(1.7013)	(1.8164)	(2.7064)	(2.2640)	(1.6131)	(1.7717)	(2.6816)
- $Spring_2$	0.7837	5.3274*	11.0099**	0.7371	0.4757	1.8932	0.1784	5.5165**	0.3302	1.6946	-0.4576	6.0050**
	(1.9530)	(3.0460)	(4.7253)	(2.4706)	(2.4091)	(1.9919)	(2.0417)	(2.7778)	(2.3418)	(1.9576)	(2.0842)	(2.8751)
- $Summer_2$	5.1621**	-2.5709	-5.6552	3.8683	7.4805***	2.3240	1.8192	-3.3839	5.6980**	1.6187	1.5977	-4.8762
	(2.0814)	(3.2057)	(4.5409)	(2.4260)	(2.5449)	(2.2247)	(2.3293)	(3.0803)	(2.3411)	(2.1918)	(2.5168)	(3.3572)
- $Fall_2$	0.0930	0.8189	2.6989	3.1931	0.3763	3.3505	-0.2199	3.5449	2.2224	5.1714*	1.4630	5.2473**
	(2.3957)	(2.1788)	(3.2682)	(3.5829)	(3.7494)	(3.2145)	(3.6881)	(2.7686)	(3.7357)	(3.0164)	(3.3410)	(2.6194)
	(2.2820)	(1.1757)	(1.5359)	(2.7593)	(3.7655)	(2.7723)	(2.5972)	(1.8875)	(3.7135)	(2.5790)	(2.2347)	(1.7417)
Observations	17,326	17,326	17,326	17,326	17,326	17,326	17,326	17,326	17,326	17,326	17,326	17,326
Number of id	141	141	141	141	141	141	141	141	141	141	141	141
RMSE	9.068	9.049	9.049	9.066	9.065	9.070	9.058	9.072	9.063	9.069	9.058	9.069
Rho	0.256	0.259	0.265	0.258	0.257	0.258	0.259	0.256	0.258	0.259	0.258	0.259
Within R-squared	0.943	0.943	0.943	0.943	0.943	0.943	0.943	0.943	0.943	0.943	0.943	0.943
Between R-squared	0.903	0.902	0.899	0.902	0.902	0.902	0.902	0.903	0.902	0.902	0.902	0.902
Demeaned Model R-squared	0.931	0.931	0.931	0.931	0.931	0.931	0.931	0.931	0.931	0.931	0.931	0.931
Full Model R-squared	0.949	0.949	0.949	0.949	0.949	0.949	0.949	0.949	0.949	0.949	0.949	0.949

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 2. *Model summaries of cattle market price in dollars per one-hundred pounds as predicted by seasonal rainfall and drought index*