Evaluating Alternative Drought Indicators in a Weather Index Insurance Instrument

TRAVIS M. WILLIAMS

*Earth Lab, Cooperative Institute for Research in Environmental Science, and Department of Geography,
University of Colorado Boulder, Boulder, Colorado*

WILLIAM R. TRAVIS

*Earth Lab, Cooperative Institute for Research in Environmental Science, and Department of Geography,
University of Colorado Boulder, and Western Water Assessment, Boulder, Colorado*

(Manuscript received 23 September 2018, in final form 16 May 2019)

ABSTRACT

Weather index insurance is a popular means of mitigating agricultural risks. Drought is a significant cause of lost agricultural production, and so precipitation index–based plans are common. Simple “percent of normal” indices are often used because they are easy to calculate and communicate to policyholders. However, the ability of such indices to reflect production losses is limited, reducing the ability of insurance to efficiently mitigate risk. This is especially true in rangeland livestock production given the cumulative effects of rainfall and other factors on range production and the complex relationships between range and livestock weight gain, which is the rancher’s main product and source of income. More sophisticated drought indices incorporate the complexities of drought into their design and would, in theory, serve as more appropriate payment triggers. This study uses a suite of drought indices to test correlation with production and the behavior of insurance based on those indices. Payout patterns based on each index were simulated within the actuarial framework of a precipitation-based insurance program aimed at livestock producers. Results were compared with the program’s precipitation index, showing that drought indices have higher correlations with range production, a tendency to incentivize growing-season protection, more even geographic distributions of risk, reduced policyholder ability to seek higher payments through strategic coverage choices, and increased provider ability to adjust payment patterns to reduce the risk of nonpayment given loss.

1. Introduction

Weather index insurance instruments are spreading around the world ([Greatrex et al. 2015](#)), offering ease of application and a relatively simple actuarial design. Index insurance uses a single indicator, like rainfall, to stand for losses caused by extreme conditions ([Conradt et al. 2015](#)). An index insures only one cause of loss and, because it is not influenced by policyholder decision-making, managerial strategies cannot increase the chance of payment, reducing costs associated with systemic risk and advantage-seeking behavior of policyholders possible in loss-based insurance ([Vedenov and Barnett 2004](#)). An independent index also reduces

information discrepancies between the insured and insurer, since the insurer provides the information, reducing the potential for adverse selection: when higher risk populations purchase more policies than lower risk groups. This design also reduces administration costs like loss verification. These features combine to increase program efficiency and expand potential coverage.

However, use of a proxy for loss introduces other complications. The efficacy of such insurance depends on the correlation between index and loss, and no index is perfectly correlated ([Miranda 1991](#); [Miranda and Gonzalez-Vega 2011](#); [Vroege et al. 2019](#)). A poorly correlated index will not pay reliably following loss and will frequently pay when unnecessary. This mismatch is termed “basis risk” and represents the primary concern of weather-based insurance research. Basis risk adheres to an index not reflective of the insured’s location (e.g., for an index interpolated from sparse data) ([Woodard and Garcia 2008](#); [Ritter et al. 2014](#)) or derives from poor

Denotes content that is immediately available upon publication as open access.

Corresponding author: William R. Travis, william.travis@colorado.edu

DOI: 10.1175/WCAS-D-18-0107.1

© 2019 American Meteorological Society. For information regarding reuse of this content and general copyright information, consult the [AMS Copyright Policy](#) (www.ametsoc.org/PUBSReuseLicenses).

correlation between the index and the product insured (Nadolnyak and Vedenov 2013). These can be distinguished as “geographic” and “production” basis risk, respectively (Ritter et al. 2014). Additionally, a “temporal” basis risk, associated with plant phenology, occurs with inappropriate time periods of coverage availability (Dalhaus and Finger 2016). While the capacity of index insurance to protect against hazard depends on minimizing basis risk, other elements must be considered. Index-based plans are also subject to behavior of the index, expectations of policyholders, and interactions among the index, actuarial criteria, and program stipulations that can yield counterintuitive outcomes (Müller et al. 2011; Daron and Stainforth 2014).

Most index insurance programs designed to mitigate drought-induced loss in agriculture are based on a simple rainfall index (Leblois and Quirion 2013). This can be troublesome due to the incomplete relationship between the meteorological drought that the index detects and the agricultural drought that causes loss (Black et al. 2015). In the case of livestock ranching, the focus of our study, ecological factors in addition to climate that affect production of the perennial grasses, forbs, and shrubs that comprise the range resource worsen the problem of linking production to an index (Heitschmidt et al. 2005; Moran et al. 2014; Knapp et al. 2015). In theory, drought indices, because they incorporate multiple variables (e.g., temperature, precipitation, soil water holding capacity, etc.) and capture the cumulative, long-term effects of moisture deficiency, better indicate the impacts of drought than would a simple rainfall index. Fidelity to drought impacts is indeed the *raison d'être* of these products. The presence of many such indicators begs the questions: Could a functional range insurance program be designed around a drought index? How would insurance payments respond to features built into these more complex indices? Which of these features are problematic in an insurance setting, and which lead to improvements over a rainfall index-based plan?

To explore these questions, we developed a simulated rainfall insurance instrument fashioned after the U.S. Department of Agriculture (USDA) “Pasture, Rangeland, Forage” (PRF) insurance (<https://www.rma.usda.gov/Policy-and-Procedure/Insurance-Plans/Pasture-Rangeland-Forage>). Administered by the USDA Risk Management Agency (RMA), PRF is designed to mitigate financial impacts of precipitation deficits on cattle ranches. Indemnities are triggered by selected thresholds of precipitation deviations from long-term averages. By simulating spatial and temporal distributions of potential payouts over the contiguous 48 states (CONUS), we compare the performance of this rainfall index instrument with several drought indices within PRF’s actuarial structure.

2. Pasture, rangeland, and forage insurance

The PRF is designed for loss mitigation in both rangeland livestock and hay production; only the rangeland provision is examined here. Range vegetation is grazed until animals achieve marketable weight. Reduced rangeland production due to rainfall deficits causes reduced animal weight gain and/or additional costs for supplemental feed. Stocking rates, feed purchases, and timing of sale depend on sufficient precipitation to maintain normal range forage and thus desired weight gain (Shrum et al. 2018). U.S. cattle ranchers have historically received less government assistance when dealing with drought than have crop farmers. While subsidized crop insurance has been available since 1980, little income protection has been available to ranchers, whose range production losses are difficult to document. The PRF is designed to fill this gap and is now is the largest weather-index based agricultural insurance program in the U.S. with premiums totaling almost \$2.5 billion, placing it fifth among Federal Crop Insurance Programs, behind corn, soybeans, wheat, and cotton since its inception in 2007 (U.S. Department of Agriculture 2018c).

a. The rainfall index

The PRF rainfall index (RI) is based on the National Oceanic and Atmospheric Administration Climate Prediction Center Unified Gauge-based Analysis of Daily Precipitation gridded product (National Oceanic and Atmospheric Administration 2017). Data are originally published in millimeters per day and interpolated to a 0.25° by 0.25° grid. Data are averaged into 2-month periods, resulting in 11 overlapping intervals (January–February, February–March, etc.). Baseline average values for each grid cell and bimonthly interval between 1948 and 2 yr prior to each insurance year are used to derive the index (U.S. Department of Agriculture 2017b). An index value, therefore, reflects the percentage of the 1948-to-present average precipitation for a specific location and bimonthly interval.

b. Indemnification process

Policyholders receive a payout if the RI falls below a certain threshold. This “strike” value ranges from 70% to 90% in 5% intervals chosen by the policyholder in advance of the insured year. Premiums are subsidized at rates dependent on the strike level, with the lowest strike level receiving 59% subsidization and the highest 51% (U.S. Department of Agriculture 2018a). Higher strike levels increase premiums and decrease subsidies but also increase the chance and magnitude of payout. The degree to which the index falls below the baseline affects the magnitude of payout. This ratio, referred to

as the “payment calculation factor” (PCF), is the difference between the strike and observed index value, divided by the strike for values below that strike level:

$$\text{PCF}_{s,l,t} = \max\left(\frac{\text{Strike}_s - \text{WI}_{l,t}}{\text{Strike}_s}, 0\right), \quad (1)$$

where $\text{WI}_{l,t}$ is the weather index value for a policy at location l during insurance interval t and s is one of a vector of possible strike levels: 0.70, 0.75, 0.80, 0.85, and 0.90.

The policyholder must choose how to allocate coverage among eligible intervals, avoiding consecutive intervals so that the same month is not covered twice. The proportion of coverage that may be placed in any one interval is constrained, with a minimum of 10% and a maximum that ranges geographically from 50% in the South to 70% in the North. For example, 30% of coverage could be allocated to the March–April interval, 30% to May–June, and 40% to July–August.

The total possible protection for a given interval and grid cell reflects productivity of the land and the value of the policy itself. A per-acre (1 acre = 0.4 ha) base value is set for each county and is lower in the West than in the East where livestock carrying capacities are higher (U.S. Department of Agriculture 2018a). Policyholders choose the acreage to be covered and can adjust the protection amount by a “productivity factor,” ranging from 60% to 150%. That product is multiplied by the portion of total coverage allocated to an interval and the bimonthly protection amount becomes

$$\begin{aligned} \text{Protection}_{s,l,t} = & \text{Base County Value}_{l,t} \times \text{Acres}_l \\ & \times \text{Strike}_s \times \text{Allocation}_{l,t} \\ & \times \text{Productivity Level}_l \end{aligned} \quad (2)$$

for a given strike level s at location l and time period t . When the index falls below the strike level, this protection amount is adjusted by the PCF to generate the indemnity function such that

$$\text{Indemnity}_{s,l,t} = \text{PCF}_{s,l,t} \times \text{Protection}_{s,l,t}. \quad (3)$$

3. Rationale for drought index–based insurance

Given the limitations of rainfall to indicate agricultural losses and that drought indices are specifically designed to reflect such impacts, it is logical to consider drought indices as insurance triggers. When asked why the PRF is not linked to the popular U.S. Drought Monitor (USDM) to trigger payments, the RMA explains that the USDM

includes multiple factors to categorize drought and is inappropriate because the PRF is a “single-peril program” (U.S. Department of Agriculture 2017a). But the USDM is also not technically an index: it is a categorical description generated from quantitative drought indicators and judgements of regional experts (Svoboda et al. 2002). Also, because it is not indexed, a USDM value is not necessarily relative to normal conditions. Although it could be indexed, USDM drought values are not continuous and extend only back to 2000, a short climatological baseline. While it might be possible to account for the former issue (see Lorenz et al. 2017), it would be impossible to extend the USDM earlier, given its real-time expert input. The RMA also perceives the USDM, and by extension drought indices in general, as reflective of multiple perils that are difficult to work into a simple actuarial system, as revealed by the history of the Multiple Peril Crop Insurance program (Knight and Coble 1997; Goodwin and Smith 2013). Like the USDM, most drought indices are calculated using multiple variables (e.g., precipitation, temperature, wind speed, relative humidity, etc.), but they are quantitative, continuous, and have long climate histories. We would argue that a multifactor drought index should not be conflated with a “multiperil” metric: each factor gives weight to a singular measure of *water deficiency*, the underlying peril.

The PRF’s RI is categorized as a “percent of normal index” in the literature (Zargar et al. 2011). Its simplicity is advantageous for communicating drought to policy holders, but it lacks statistical transformation to account for a heavily skewed value distribution. This discrepancy can be seen in the histogram of RI values (Fig. 1); the most common value is around 80% of “normal” rainfall. Another criticism is the RI’s inability to account for regional differences in impacts (Keyantash and Dracup 2002; Hayes 2006; Zargar et al. 2011). While drought indices may be more complicated to interpret, many are well known in agriculture, are no more complex than the USDM, and incorporate methods to account for skewed distributions and the relativity of impacts to location.

A benefit of index insurance is its ability to mitigate risk when production is not routinely measured directly, as in rangeland livestock production where the marketed product, livestock, is based on the insured but poorly measured product, forage (Vroeghe et al. 2019). However, a few regional- and local-scale studies do compare various indices with rangeland variability. Maples et al. (2016) examine a program using the RI to insure grasses and small grains grown and marketed for livestock feed. They correlate the RI and forage growth at three locations in Oklahoma, finding that coefficients are low and sometimes negative. Another study correlates four different indices with dryland wheat yield

FIG. 1. The value distribution of the rainfall index. The bin size was set at a very small value to reveal a peak in zero counts. A break along the x axis illustrates the long tail resulting from infrequent but large rainfall events.

(a proxy for grassland production) across 43 crop districts in the Canadian Prairie from 1961 to 1999 (Quiring and Papakryiakou, 2003). It finds that the Palmer Z index better correlates with production than the Palmer drought severity index (PDSI), the standardized precipitation index (SPI), and the NOAA drought index (NDI). A later study also found that the Z index correlates better than the PDSI with wheat production and that the SPI and the standardized precipitation–evapotranspiration index (SPEI) demonstrate improvements over the Z index, with the SPEI doing best (Vicente-Serrano et al. 2012). In a literature review of indices likely to best capture drought impacts on the Texas High Plains, Moorhead et al. (2015) also settle on the SPEI.

4. Alternate index experiments

Here we conduct a large-scale test of alternative drought indices. First, the correlation of each index with hay and wheat production, and rangeland production modeled by the U.S. Forest Service, is calculated to test its ability to reflect actual loss. Second, a simulation of the historical RI under current provisions of the PRF is used to create a time series of payments for every PRF grid location in the CONUS. These potential payments would have occurred for each bimonthly interval under a particular set of policy selections (e.g., acreage and productivity factor) for each location based on

RMA actuarial rates for the 2018 insurance year. We then simulate how payouts would be distributed if the insurance program was linked to alternative drought indices in place of the RI. Indices tested are the PDSI; the self-calibrating PDSI (PDSI-SC); the Palmer Z index; the 1-, 2-, 3-, and 6-month SPI; and 1-, 2-, 3-, and 6-month SPEI. Payout distributions based on these indices are also compared for seasonal patterns of payment, since allocation of coverage among intervals is an important choice by policyholders.

a. Alternative drought indices

The PDSI, developed in 1965 by W. C. Palmer, was selected because it is a well-known drought index. PDSI calculates deviations from the precipitation needed to maintain locally normal soil moisture based on precipitation, temperature, and estimates of soil water holding capacity. It is also designed to simulate the cumulative nature of drought by weighing previous PDSI values on current values (Palmer 1965). Computational constraints and data availability restricted the local specificity that Palmer was able to incorporate, so the PDSI-SC was developed by Wells et al. (2004) to replace certain constants in the PDSI algorithm with observations of the PDSI itself. The Z index is the nonautoregressive portion of the PDSI, calculated over a single month, and is often referred to as the soil anomaly index (Palmer 1965). The SPI is a multi-scalar precipitation index that captures the cumulative nature of drought using a customizable time window of

calculation, allowing users to select the length most important to particular impacts. Where the RI uses a simple percentage of mean rainfall, the SPI fits observations probabilistically to a gamma distribution and transforms the results to a standard normal distribution (McKee et al. 1993). The SPEI is another multiscalar, probabilistic, and standardized index that also incorporates temperature to estimate water loss from evapotranspiration and fits the resulting values to a log-logistic curve (Vicente-Serrano et al. 2010). These multiscalar indices are referred to as SPI- X and SPEI- X , where the suffix value X indicates the number of months over which the index is calculated. Drought index data were acquired through the Western Regional Climate Center (Abatzoglou et al. 2017).

b. Production correlations

To test the ability of each drought index to explain variance in production we employ a convergence of evidence approach to compensate for the limited data on range production. We correlate each index with closely related proxy crop yields obtained via the USDA National Agricultural Statistics Service (NASS) Quick Stats 2.0 (<https://quickstats.nass.usda.gov/>; accessed May 2018) for nonirrigated hay and dryland wheat. We then do the same with the U.S. Forest Service's "Rangeland Vegetation Simulator" (RVS), a relatively new product that estimates U.S. rangeland production.

Nonirrigated hay production data are available in tons (1 ton = 907 kg) per acre for selected counties in Colorado, Montana, and Wyoming from 1959 to 2008. Dryland wheat yield data are available in bushels (1 bushel of wheat = 60 lb = 27.2 kg) per acre for a much wider area and a longer time period for counties in several Western and central states from 1929 to 2007. The RVS calculates annual rangeland production for the western and central United States by combining normalized difference vegetation index (NDVI) values with precipitation data and site-specific biophysical settings (Reeves 2016). The RVS includes precipitation as an input, thus reducing the independence of its production values from the drought indices, but only annual precipitation is included and is not standardized while temperature and evapotranspiration are not used. The RVS is validated with direct measurements of rangeland production values from the National Resource Conservation Service Soil Survey Geographic dataset (SSURGO; Reeves 2016). RVS data are consistent from year to year and are available from 1984 to present, thus providing the most comprehensive assessment of rangeland productivity in the United States.

To correlate hay and wheat production data with each index, annual production was joined with a spatial county layer and transformed into a time series of grids

TABLE 1. The average correlation between various drought indices and annual hay and wheat production for 1959–2007.

Hay		Wheat	
Drought index	Avg correlation	Drought index	Avg correlation
SPI-6	0.4849	SPI-6	0.2774
SPEI-6	0.4769	PDSI	0.2718
Z index	0.4535	PDSI-SC	0.2631
PDSI	0.4481	SPEI-6	0.2622
PDSI-SC	0.4267	Z index	0.2608
SPI-3	0.4264	SPI-3	0.2488
SPEI-3	0.4133	SPI-2	0.2422
SPI-2	0.409	SPI-1	0.2338
SPEI-2	0.3983	SPEI-3	0.2292
SPI-1	0.3929	SPEI-2	0.2216
SPEI-1	0.3863	RI	0.2131
RI	0.3188	SPEI-1	0.2119

with a resolution that matches the PRF grid. Bimonthly values of each index were then averaged annually to match the RI. In each cell, for each index, a Pearson's correlation coefficient was calculated between each average annual drought index and production. The average value of these coefficients was then calculated for each index to allow for comparison. To examine possible trends over time two periods were used: the longest shared record from 1959 to 2007 (Table 1) and a more recent record from 1984 to 2007 (Table 2).

For the RVS, which is already a gridded product, the data were simply transformed to match the spatial resolution and extent of the RMA grid before performing the same correlation method as with hay and wheat. Two time periods were also used here: 1984–2007 (Table 2) to compare directly with NASS production and 2000–16 to match the more recent study period of the insurance simulations (Table 3).

c. Insurance simulation methods

To simulate PRF payouts, actuarial information was acquired through RMA's information browser for the 2018 insurance year (U.S. Department of Agriculture 2018a). Rainfall index, indemnity, and premium calculations were validated using the RMA's online decision support tool (U.S. Department of Agriculture 2018b). To compare the PRF with alternate drought indices, raster data for each index over the CONUS were re-sampled using the bilinear method to 0.25° cell sizes and values at each cell were combined into overlapping bimonthly means to match the spatial and temporal structure of the PRF rainfall index. RMA grid identifier, county base values, and bimonthly allocation limits were associated with the appropriate cell and month. The rainfall indexing process results in an overall distribution of values with a right skew and an uptick in

TABLE 2. The average correlation between various drought indices and annual RVS, hay, and wheat production for 1984–2007.

RVS		Hay		Wheat	
Drought index	Avg correlation	Drought index	Avg correlation	Drought index	Avg correlation
SPI-6	0.4006	SPEI-6	0.5596	SPI-6	0.258
SPEI-6	0.3692	SPI-6	0.5535	SPEI-6	0.2552
Z index	0.3616	PDSI	0.5442	PDSI	0.2467
SPI-3	0.3363	Z index	0.5286	Z index	0.2424
PDSI	0.3238	PDSI-SC	0.5228	PDSI-SC	0.2365
SPEI-3	0.3116	SPEI-3	0.4782	SPI-3	0.2242
SPI-2	0.3116	SPI-3	0.4769	SPEI-3	0.2156
PDSI-SC	0.2992	SPEI-2	0.4496	SPI-2	0.2115
SPEI-2	0.2882	SPI-2	0.4476	SPEI-2	0.2041
SPI-1	0.2781	SPEI-1	0.4319	SPI-1	0.1987
SPEI-1	0.2602	SPI-1	0.4239	SPEI-1	0.1917
RI	0.2194	RI	0.3178	RI	0.1695

probability as values approach zero (Fig. 1). The presence of a high number of low values results in a higher chance of payment triggers, larger PCFs, and, absent actuarial adjustment, higher overall payments compared to an index with a normal distribution.

5. Necessary adjustments to compare indices

To apply the PRF criteria to alternative indices it was necessary to make adjustments to both. The purpose of this study is not to create a fully functional drought insurance program but to compare the general behavior of weather indices in an insurance system, so we do not alter the indices greatly; doing so would risk losing the features of a drought index that make it desirable. One problem is that drought indices are centered on zero, have no lower limit, and each has a unique scale of measurement, while the rainfall index nicely yields percentages. It might be possible to simply index each drought index with their own historical averages and retrieve percentages, but as the indices are already indexed this strategy yields questionable results.

Any insurance scheme based on drought indices would have to account for these issues, set actuarial rates accordingly, and adjust calculation strategies to result in economically sound indemnifications. Insurers can adjust policy stipulations and rates, but the underlying behavior of the index is crucial to the fidelity to the actual weather or climate risk. Three aspects were changed, leaving the bulk of the PRF structure intact.

a. Truncating outliers

Drought indices can exhibit extreme low values. For example, the SPEI-2 generally ranges from -2.5 to 2.5 but has fallen below -7 at least twice since 2000 (both in a cluster of low values in Texas during 2011), meaning that unreasonably high payments could result from drought

index-based insurance when compared with the RI. The issue is somewhat mitigated when monthly values are summed into bimonthly bins, but is still problematic, particularly for the SPEI-2+ and for the PDSI. To mitigate this, values more than 3 standard deviations from the average of each index were truncated and assigned the value at 3 standard deviations.

b. Matching strike levels

For comparability, strike levels of each drought index were set at values with equal probability of occurrence to those of the RI. For example, the overall probability of experiencing an RI below 70% is the same as an SPEI-2 value below -0.62 (Fig. 2). It was also necessary to standardize each drought index to a common scale to make comparison possible and avoid negative numbers. Each index was standardized to a scale from 0 to 1. The strike value in the example above, 70%, becomes 0.41 in a distribution with a mean of 0.50. While these values may not match exactly the drought severity categories conceived by the climatologists who designed them, this

TABLE 3. The average correlation between various drought indices and annual RVS production for 2000–16.

Drought index	Avg correlation
SPEI-6	0.5348
SPI-6	0.5177
Z index	0.4982
PDSI	0.4799
PDSI-SC	0.4703
SPEI-3	0.4635
SPI-3	0.4501
SPEI-2	0.4423
SPEI-1	0.4267
SPI-2	0.4258
SPI-1	0.4034
RI	0.3011

FIG. 2. The (left) RI value distribution with the 70% strike level marked compared with (right) an alternative drought index (the 2-month SPEI) binned into bimonthly intervals with outliers assigned to 3 standard deviations above and below the mean and a strike level set at -0.62 , which occurs at a probability that is equal to the 70% strike level in the RI.

step allows the drought indices to function within the structure of the PRF comparably to the RI.

c. Scaling payments

Potential payments generated using the above strategy were consistently smaller than those generated by the RI. National average dollar amounts were between 26% and 87% of the average RI payments. This depended mostly on the index, with also some differences between strikes levels. For example, the ratio between the average SPI-1 payment and the average RI payment at the 70% strike level was around 0.61, whereas at the 90% level the ratio was around 0.87.

To improve comparability of payouts, a scalar term unique to each index and strike level was added to the indemnity calculation to imitate an actuarial system that would apply detailed pricing, risk, and socioeconomic considerations. This scalar was calculated as the ratio between average national payout potential at each strike level of the RI and each alternative drought index (DI) for PRF baseline period 1948–2016. For any individual DI at a strike level s ,

$$\text{DI Scalar}_s = \frac{1/(NT) \sum_{l=1}^N \sum_{t=1}^T \text{RI Indemnity}_{s,l,t}}{1/(NT) \sum_{l=1}^N \sum_{t=1}^T \text{DI Indemnity}_{s,l,t}}, \quad (4)$$

where N is the number of RMA grid cells (13 225) and T is the number of insurance intervals in the study period ($11 \times 17 = 187$). The final calculated indemnity resulting from a DI at any particular s becomes the product of the PCF, total protection, and these two scalar terms:

$$\text{Final DI Indemnity}_{s,l,t} = \text{Initial DI Indemnity}_{s,l,t} \times \text{DI Scalar}_s. \quad (5)$$

The nationwide average payment potentials are compared with the original potentials in Fig. 3. The resulting payments range from 105% to 95.2% of the RI. When this payment scaling step is combined with the strike level matching step described above, the resulting payouts have similar chances of occurrence and similar average values, leaving features such as seasonality and variance free to vary.

6. Index performance assessments

The same feature of a weather-based index that generates payouts also generates risk and uncertainty for the policyholder: variability. The rainfall index indemnifies more with larger variance in bimonthly precipitation (Fig. 4).

Although the RMA advises policyholders to insure the most important months for their rangeland, financial

FIG. 3. (a) Nationwide average PRF-like potential payouts resulting from each index at each strike level before scaling. (b) Average payouts after scaling each individual payout by a ratio designed to reflect adjustments to county base values that would be required to administer a similarly funded program.

incentives exist not to do so. The probability of indemnification increases by selecting intervals with the most variance in rainfall, regardless of their importance to forage production, and many locations exhibit a set of intervals that pay more over time. Such patterns can be exploited to maximize payments rather than to minimize risks (Smith and Watts 2009). Westerhold et al. (2018) recognize this possibility in assessing the risk-reducing capacity (i.e., reduced revenue variance) of various PRF interval selection strategies using production data from two Nebraska sites. They find that the largest risk reductions correspond with the selection of intervals with the highest average rainfall, the growing season in this case. This contrasts with strategies resulting in the highest revenues, which correspond with the low precipitation, nongrowing-season months.

Diersen et al. (2015) found similar results in South Dakota where a risk-minimizing strategy required insurance of particular summer months while a revenue-maximizing strategy required placing coverage in early winter and fall, a strategy that increased revenues by about 60% and the standard deviation of revenues by nearly 300% over the optimal risk reduction strategy. Correspondence with private insurers and the RMA verify that such strategic interval choice does occur. Westerhold et al. (2018) suggest limiting the availability of such problematic intervals, but these strategies could be helpful to policyholders in locations with low growing-season rainfall variability who cannot afford both insurance premiums and an elevated risk of nonpayment during drought. Such restrictions are unpopular with policyholders, and thus it would be

FIG. 4. (a) Geographic distribution of the coefficient of variation (label CV) resulting from the RI for 1948–2016 at the 80% strike level. (b) Geographic distribution of average PCFs of the RI from 1948 to 2016.

preferable if the index itself naturally incentivized growing-season selection.

To compare seasonal payment patterns and the incentive for strategic interval selection, payment from four seasonal allocation plans and a profit-maximizing selection strategy are simulated for each grid cell between 2000 and 2016 using a hypothetical 50% allocation of coverage to each interval for a 500-acre ranch at the middle (80%) strike level. Four maps of results from splitting protection between two intervals in each season are generated. Potential payments are also calculated based on the two intervals with the highest average PCF since 1948 as a profit maximizing scenario. To paint a fuller picture of the seasonal incentive structures for each index on a national scale, maps of the highest PCF intervals are created along with the percentage of area in the spring and summer (intervals 3–7) for each. To illustrate the differences in resulting payout patterns between the rainfall index and a selected drought index on a local scale, four sample locations representing active cattle markets in a variety of geographies were analyzed: Billings, Montana; Coleman, Texas; Kearney, Nebraska; and Oklahoma City, Oklahoma. The same hypothetical policy described above is used for each location.

To assess distributions of the underlying risk involved with each index, maps of average PCF values at the 80% strike level across all intervals were generated for each index for the study period 2000–2016. To assess how these distributions change over time, PCF maps were also generated for the full RI record used in the PRF, 1948–2016.

7. Results

a. Production correlations

Correlation between indices and production varied by time period and crop, ranging from 0.17 to 0.28 for wheat, from 0.32 to 0.56 for hay, and from 0.22 to 0.53 for the

RVS (Tables 1, 2, and 3). The RI shows the lowest correlation with production in each case except for 1959–2007 wheat yields (Table 1). Indices with longer time scales generally result in higher coefficients for all crops and time periods, with the 6-month standardized indices (SPI and SPEI) consistently performing best. The Palmer Z index is an exception to this pattern; despite being a 1-month index it consistently ranks among the other Palmer indices in the top five. While coefficient magnitude varies, the ranked order of index correlations is generally maintained between crops and time periods. Among the standardized indices in the first period (1959–2007), there is a bias against the inclusion of evapotranspiration as the SPIs outperformed their SPEI counterparts at each time-scale. In the middle time period (1984–2007) this bias persists for wheat and the RVS but is reversed for hay and the SPEI-6 correlation takes over the top ranking for hay. In the most recent period (2000–16), the RVS also reverses that pattern with each SPEI outperforming its SPI counterpart. This hints at an increasing importance of the inclusion of temperature in indicators of range production.

For the RVS in this most recent study period, the 1-month SPI, which is most similar to the RI among these indices, shows the second lowest correlation. The 6-month SPEI gives the highest coefficient, corroborating results by Vicente-Serrano et al. (2012) and Moorhead et al. (2015). The 6-month SPI is second, suggesting the importance of both temperature and longer calculation time scales. The Z index is third and by performing better than the PDSI corroborates Quiring and Papakryiakou (2003) and Vicente-Serrano et al. (2012).

b. Seasonality

Seasonal PCF biases for the RI emerge in large regional clusters (Fig. 5f). The central states and peninsular

FIG. 5. Geographic distributions and national means of potential PRF-like payments for rainfall-based policies at an 80% strike level with protection split between pairs of (a) winter, (b) spring, (c) summer, and (d) fall insurance intervals and (e) with an “optimal” strategy whereby protection was split between whichever two intervals yielded the largest average payment calculation factors for 1948–2016. (f) The intervals with the largest average PCF value to illustrate the process of determining the optimal strategy.

Florida both show a bias to the November–December interval, whereas virtually all of the rest of the East is grouped in one of the two preceding fall intervals. PCF bias in the Northwest is strongest in July–August, whereas the June–July interval dominates the Southwest. Elsewhere, clusters of high profit-maximizing strategy payments mirror those of the bimonthly PCF biases, with large groups in the northwestern, southeastern, and central regions. Of the five interval selection strategies tested, the profit-maximizing strategy results in, by far, the highest potential payments: an average of \$2,271. Winter-season interval selection results in the second highest (\$918), and fall selection results in the third highest (\$873). The spring and summer combinations, which match the grassland growing season in much of the

nation, resulted in the lowest potential payments with average values of \$795 and \$770, respectively (Fig. 5).

SPEI-1 was chosen for detailed seasonality comparisons to the RI because it has the same time-scale, but incorporates temperature. SPEI-1 reverses the RI seasonal pattern, with the highest-paying interval combination in summer (\$1,063) and then spring (\$858). Winter resulted in the lowest potential average payout (\$721). At \$2,357, the profit-maximizing strategy with the SPEI-1 resulted in somewhat higher payment than the RI (Fig. 6).

The second simulation reveals that all drought indices have much larger geographical extents of growing-season PCF bias, comprising 45%–66% of the CONUS as compared with 26% for the rainfall index (Fig. 7). Growing-season bias diminishes for the PDSI, PDSI-SC,

FIG. 6. As in Fig. 5, but for 1-month SPEI-based policies.

and RI as strike levels increase, but it increases for all other indices. The PDSIs show spring and summer bias over the majority of the West but would incentivize winter protection for most of the East. The Z index incentivizes the spring and summer across the largest CONUS area: 66% at the 80% strike level.

National potential payments from the profit-maximizing interval selection strategy are lower than the RI for most drought indices at each strike level (Fig. 8). The exceptions are the Z index and SPEI-1, which pay more across the strike levels than the RI using this strategy, and the PDSI-SC, which pays 2.5% more at the 70% strike. The SPI-based plans show the largest reductions from the profit-maximizing strategy, averaging 18.4% across each strike level. In terms of seasonality, each index shows a reduction in winter payout bias at all strike levels relative to the RI, with the largest for the SPI-3 (Fig. 9).

The Z index and SPEI-1 result in the largest summertime payment increases over the RI at 46.8% and 38.7%, respectively. The PDSI-SC- and SPEI-based plans result in the highest springtime payment increases, averaging 15.9% and 14.9%, respectively. For the fall strategy, all of the SPI indices pay less than the RI, with an average 6.9% reduction, while the SPEI-6 exhibits the largest average increase at 24.5%. If spring and summer are considered to be the growing season and winter and fall the nongrowing season, the overall potential payment ratio between the growing and nongrowing seasons is highest for the Z index, the SPEI-1, and SPEI-2, at 1.25, 1.24, and 1.23, respectively. The three lowest are the RI, PDSI, and PDSI-SC at 0.88, 0.97, and 1.00, respectively.

Local RI-based payment patterns reflect the national indemnity trends described above. Kearney's February–March interval has significantly higher payout potential,

FIG. 7. PRF insurance intervals with the highest average payment calculation factors values at the 80% strike level for 1948–2016. The percentage of total CONUS area for which this value falls in the spring and summer intervals (intervals 3–7) is given for each map.

and the November–December intervals pay most at both Oklahoma City and Coleman (Fig. 10). None of the winter or fall intervals yield the highest payout potential for the SPEI-based policies. The top-paying intervals for this experimental plan are July–August for Billings, April–May for Kearney, June–July for Coleman, and March–April for Oklahoma City. In every case the SPEI

incentivizes the spring or summer months while the rainfall index incentivizes the winter.

c. Payment timing

The RI payment pattern is marked by frequent, relatively small payouts, often in the winter and fall, across all sites. The SPEI-based instrument pays somewhat less

FIG. 8. Average potential PRF-like payments from each index at each strike level (70%, 75%, 80%, 85%, and 90%) for the winter, spring, summer, fall, and optimal interval allocation strategies. Note the scale differences.

FIG. 9. Average potential payments from each index for each of the seasonal strategies averaged across all strike levels.

frequently, though often matches the rainfall-triggered payouts in spring and summer. While the individual payments tend to be larger for the SPEI, this does not fully compensate for lowered frequency as the RI yields higher total payment potential at each site (Fig. 10). The time series of payments from the longer-term drought indices show a very different pattern. The longer the “memory” of the index, the more grouped the payments, with more payments during droughts and fewer in between. This pattern is evident in the two multiscale indices examined here (see Fig. 11 for an example).

Billings shows clustering of potential payouts in 2003, 2006, and 2012 that is shared between the RI and the SPEI-1; the SPEI results in higher payments during each cluster while the RI pays more frequently between clusters. The RI would have paid in almost every interval between mid-2000 and early 2005. In Coleman, the patterns of payout are very similar among indices, though the RI triggered significant payouts in winter of 2013–14 when the SPEI paid very little. The 2010–11 drought was detected by both indices, but the SPEI payouts during this period were considerably larger. In Kearney the SPEI triggers relatively few payments and diverges considerably from the RI. The SPEI-1 at this location pays little during winter intervals, when most RI payments occur.

While the PDSI is not scalable, it is parameterized for autoregression, ranging from 2 to 9 months depending on location (Guttman 1998). In Coleman (Fig. 12), where droughts were experienced in 1999–2000, 2005–06, 2008–09, and 2010–11 (Nielsen-Gammon 2011; National Drought

Mitigation Center 2018), the total payout potential from the PDSI-SC and the RI are relatively close at \$214,609 and \$176,441 respectively, although the PDSI-SC pays out during every interval within the drought periods described above and for only one interval in between (the July–August interval of 2001). Given the gaps in payouts from the RI, or any of the shorter-term indices, it would have been possible for an insured rancher to, by chance, choose the wrong intervals and receive little compensation during 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, a rancher in Coleman would have received \$6,070 from the RI as compared with \$18,063 from the PDSI-SC during the 2010–13 drought period. Using the RI, this rancher would have received \$2,579 for the 2008–09 drought when the PDSI-SC would have triggered \$9,448. In Billings during drought in 2012 and 2013, a rancher with the same strategy would have received \$3,383 with the RI as compared with \$7,421 from the PDSI-SC. In Kearney, the PDSI-SC payments are grouped into four distinct events: 2002, 2006, 2012, and 2016. Here, the total payment potential is \$125,594 for the RI as compared with \$74,157 for the PDSI-SC, while the potential payments from intervals 5 and 7 are \$21,219 and \$14,877, respectively. The payment grouping is even more distinct in Oklahoma City where only three events resulted in payments: 2005–07, 2011, and 2013. Here, the total payment potential is \$198,315 for the RI and \$130,056 for the PDSI-SC, although the potential payments from intervals 5 and 7 are very close at \$23,189 and \$23,051, respectively. Kearney and Oklahoma City would have experienced

FIG. 10. Time series of potential payments at sample locations from the PRF-like insurance based on the RI and the 1-month SPEI with a policy for a 500-acre ranch set at an 80% strike level and 50% protection allocation for each interval. The consistent negative values for non-payout intervals is the premium cost to be paid by the producer, which is held constant across the time series.

FIG. 11. SPI-based payments in Coleman between 2000 and 2016 at the 1-, 2-, 3- and 6-month time scales with a policy for a 500-acre ranch set at an 80% strike level and 50% protection allocation for each interval.

periods of zero PDSI-SC-based payments that lasted 5 years or more. The largest gap in potential payouts under the RI at any of the sites is only 16 months, at Kearney from the sixth interval of 2006 to the tenth interval of 2007.

d. Geographic distribution of risk

The distribution of PCF values for the RI show a distinct east–west contrast and large areas of high values in the Southwest (Fig. 13). The longer the time scale of the standardized indices, the more clustered PCF values become. PCF values from the two PDSIs exhibit a very similar pattern, though they show less risk in North-Central states and considerably more in the Rocky Mountains and Southeast. The Z index exhibits an evenly distributed pattern, suggesting an effect of autoregression in the PDSIs. The one-month SPI and SPEI indices also show PCF values spread more evenly across CONUS. The SPEI-1 still exhibits significantly higher values in the Southwest. The Southwest clustering of PCF values from the 6-month SPEI is nearly as strong as that for the RI or PDSI-SC. Additionally, PCFs from

each alternate drought index are more evenly distributed spatially than the RI at the longer time period 1948–2016 (Fig. 14).

8. Discussion

Index correlations with the hay, wheat, and rangeland production data suggest that all the selected drought indices exhibit improved ability to indicate losses in rangeland production over the RI, with the 6-month SPEI performing best. As a modeled product that incorporates precipitation, the RVS is not a fully independent comparison, but results for hay and wheat production corroborate its correlation rankings. Indices that include temperature (Palmer's and SPEIs) and those calculated at longer time scales (SPEI-3+, SPI-3+, PDSI-SC, and PDSI) tend to better reflect rangeland production, and a comparison between earlier and more recent periods indicate an increasing importance of temperature in detection of rangeland production variance.

FIG. 12. As in Fig. 10, but based on the RI and the PDSI-SC.

Correlation with loss is, however, not the only criterion important to an insurance program as large as the PRF. The RI simulations reveal a financial incentive to insure the least important months for forage growth in much of the CONUS, undermining the specificity

required for an efficient index-insurance plan. Most drought indices on the other hand showed broad payment distributions biased toward the growing season, excepting the PDSI and PDSI-SC in the East. While the SPEI-1 and Z index exhibit significant improvements in

FIG. 13. Geographic distributions of average PCFs for 2000–16 at the 80% strike level.

correlation and a growing-season bias, each of these have strong seasonal patterns that could exacerbate strategic interval selection. In contrast, the other drought indices showed lessened potential for such strategy compared to the RI. For all drought indices, however, the intervals that policyholders would be most incentivized to insure are most aligned with potential loss. This indicates that

drought indices could diminish temporal basis risk, adverse interval selection, and the need for compensatory program restrictions.

While the SPI-1, SPEI-1, and Palmer Z index exhibit higher correlations with rangeland production than the RI, like the RI they result in payout gaps during drought events, and more frequent payouts in between droughts.

FIG. 14. As in Fig. 13, but for 1948–2016.

This lends further support to the ability of drought indices with longer time scales to reflect ranch enterprise drought risk. An index with too long of a “drought memory,” though, might create problems for insurance providers. In the PRF, interval selection occurs during sign-up in the November prior to each insurance year. A program using long time frame indices would have to move this step earlier in the year to avoid adverse interval selection. The grouping of payments also creates systemic risk. This is typically thought of as problematic in loss-based insurance (Vedenov and Barnett 2004). Payout clustering, while emulating drought patterns, may be constrained by the provider’s ability to cover large outlays clustered in time and by reduced participation of policyholders during long payment-free periods. This and index predictability are both areas where multiscaleability would be useful. Because payout grouping is relative to the length of the index’s time scale, the ability of the program designers to choose any number of months allows for flexibility and ease of calibration in selecting the optimal index. A 2- or 3-month index might strike a compromise between payout certainty for policyholders and budgetary constraints on providers. Also, drought in November would have minimal influence on the subsequent year’s first interval using a 3-month index and none with a 2-month index, thus maintaining the popular enrollment period.

Statistical standardization that is common to drought indices also means that insurers will need fewer adjustments to compensate for geographic discrepancies in indicated impacts. Research shows that indemnification according to a nonstandardized, percent-of-normal scheme is highly related to base climate and will tend to pay more frequently in arid locations (Nicholls and Wong 1990; Siebert and Ward 2011; Fatichi et al. 2012). This is the case for the RI in the Southwest, as shown in the comparison between PCFs and coefficients of variation (Fig. 4). While premiums can be set to reflect this added risk, it is so severe in the Southwest the RMA has removed the eligibility of most intervals, typically when the average PCF values rose above 0.25. A standardized index will exhibit a smoother spatial distribution of risk, lessening the need for such stipulations.

Indices calculated using shorter time scales show smoother geographic distributions of risk. This is apparent in the SPEI and SPI. When calculated over a longer time period (1948–2016), however, all indices but the RI result in smoother geographic distributions of risk. This suggests that the drought index–based risk clustering present in the 2000–16 test period is affected by recent droughts. The degree to which this standardization step smooths risk, therefore, is dependent on the duration of the insurance program and the length of the index’s memory, in addition to standardization method.

Including temperature in a weather index may become increasingly important to accurately indicate rangeland production. Research indicates that, as climates warm and evapotranspiration rates increase, the impacts of drought become more difficult to discern by precipitation measures alone (Easterling et al. 2007; Vicente-Serrano et al. 2012; Heim 2017). Indeed, the SPEI was designed with global warming and temperature-driven drought in mind. The correlations of drought indices with rangeland production performed in this study suggest the same phenomenon. While the temperature-influenced SPEI is outperformed by the purely precipitation-based SPI at each of the four monthly time-scales during earlier time periods, this pattern is reversed in the 2000–16 record. Temperature may play a particularly critical role in determining drought impacts in the southwestern and south-central United States, for which several studies point to increased drought (Burke et al. 2006; Sheffield and Wood 2008; Winter and Eltahir 2012; Dai 2013; Cook et al. 2015). However, the inclusion of temperature must be handled with care in a warming climate. There is concern that drought indices using the common Thornthwaite method (TM) to derive potential evapotranspiration (PET), although performing well up to the present, may perform poorly under future higher temperature conditions (Hoerling et al. 2012; Feng et al. 2017; Dewes et al. 2017). The TM calculates PET using only temperature and latitude as inputs, so that increased temperatures can yield proportional increased drought severity even if moderating factors such as cloudiness or relative humidity are present. Feng et al. (2017) find that the Penman–Monteith method (PM) corresponds better to warming projections from Earth-system models for the Great Plains, and Dewes et al. (2017) finds that the PM is more appropriate than several other methods for calculating PET in the twenty-first century. However, Hoerling et al. (2012), also analyzing the Great Plains, claim that the temperature dependency is still too strong with the PM method. This would suggest that insurance using a drought index with either of these two popular PET calculation strategies might overestimate drought impacts in the future. Hoerling et al. (2012) suggest that future drought index algorithms should calculate PET using Earth-system models that incorporate variables such as plant phenology, canopy cover, and root interactions with groundwater. Data constraints have led to the adoption of less-complex methods, but it may soon be possible to implement such strategies in a cost-efficient manner.

9. Conclusions

Weather-based index insurance promises to provide agricultural producers affordable financial protection

from extremes. Whether this can be provided efficiently and sustainably depends on the ability of the chosen weather index to accurately indicate losses incurred by policyholders. In the case of the PRF, this would likely involve selection of a temperature-influenced standardized index that is calculated over a relatively long time scale. According to Miranda (1991), the correlation of an index with agricultural production would be the primary determinant of risk reduction for any individual producer. However, for a program that serves a large area, with a variety of geographies, climates, and policyholder expectations, this straightforward criterion is insufficient. In addition to evidence that the RI violates the assumption of high correlation with loss, other patterns in its record incentivize policyholders to insure nongrowing-season months and distribute risk unevenly across the country. Such an index requires adjustments in plan design (e.g., interval eligibility restrictions) that may impact its attractiveness to potential policyholders.

Features of the drought indices examined in this study would reduce the need for program adjustments. This family of weather indices provides more capacity to calibrate a weather insurance program to the climate, the insured product, and the limitations inherent in insuring against systemic risks. A drought index-based insurance program presents implementation challenges and would require calibration, operational testing, actuarial research, and a pilot program typical to the rollout of new insurance programs. However, our simulations point to significant potential improvements over the common RI plan by using a carefully chosen drought index.

As index insurance expands, and to improve drought loss coverage in particular, further analysis is needed into how alternative indices behave in particular geographic and climatic settings, how they interact with social behavior and expectations, and how they perform during extreme drought episodes that are likely to cause the largest losses.

Acknowledgments. Funding for this work was provided by the University of Colorado Boulder Grand Challenge for Space and Earth Sciences, which supports Earth Lab, with additional funding from the Western Water Assessment under National Oceanic and Atmospheric Administration Climate Program Office Grant NA15OAR4310144 and the National Integrated Drought Information System. Data and advice from the USDA Risk Management Agency, and discussions with Tait Berlier of AgRisk Advisors, were helpful in this project. The authors are responsible for all findings and conclusions.

REFERENCES

- Abatzoglou, J. T., D. J. McEvoy, and K. T. Redmond, 2017: The West Wide Drought Tracker: Drought monitoring at fine spatial scales. *Bull. Amer. Meteor. Soc.*, **98**, 1815–1820, <https://doi.org/10.1175/BAMS-D-16-0193.1>.
- Black, E., E. Tarnavsky, H. Greatrex, R. Maidment, A. Mookerjee, T. Quaife, and J. Price, 2015: Exploiting satellite-based rainfall for weather index insurance: The challenges of spatial and temporal aggregation. *Proc. First Int. Electronic Conf. on Remote Sensing*, 1–19, <https://doi.org/10.3390/ecrs-1-f002>.
- Burke, E. J., S. J. Brown, and N. Christidis, 2006: Modeling the recent evolution of global drought and projections for the twenty-first century with the Hadley Centre climate model. *J. Hydrometeorol.*, **7**, 1113–1125, <https://doi.org/10.1175/JHM544.1>.
- Conradt, S., R. Finger, and M. Spörri, 2015: Flexible weather index-based insurance design. *Climate Risk Manage.*, **10**, 106–117, <https://doi.org/10.1016/j.crm.2015.06.003>.
- Cook, B. I., T. R. Ault, and J. E. Smerdon, 2015: Unprecedented 21st century drought risk in the American Southwest and central plains. *Sci. Adv.*, **1**, e1400082, <https://doi.org/10.1126/sciadv.1400082>.
- Dai, A., 2013: Increasing drought under global warming in observations and models. *Nat. Climate Change*, **3**, 52–58, <https://doi.org/10.1038/nclimate1633>.
- Dalhaus, T., and R. Finger, 2016: Can gridded precipitation data and phenological observations reduce basis risk of weather index-based insurance? *Wea. Climate Soc.*, **8**, 409–419, <https://doi.org/10.1175/WCAS-D-16-0020.1>.
- Daron, J. D., and D. A. Stainforth, 2014: Assessing pricing assumptions for weather index insurance in a changing climate. *Climate Risk Manage.*, **1**, 76–91, <https://doi.org/10.1016/j.crm.2014.01.001>.
- Dewes, C. F., I. Rangwala, J. J. Barsugli, M. T. Hobbins, and S. Kumar, 2017: Drought risk assessment under climate change is sensitive to methodological choices for the estimation of evaporative demand. *PLOS ONE*, **12**, e0174045, <https://doi.org/10.1371/journal.pone.0174045>.
- Diersen, M., P. Gurung, and S. Fausti, 2015: Optimal allocation of index insurance intervals for commodities. *Proc. Southern Agricultural Economics Association Annual Meeting*, Atlanta, GA, SAEA, 19 pp., <https://ideas.repec.org/p/ags/saea15/196793.html>.
- Easterling, D. R., T. W. R. Wallis, J. H. Lawrimore, and R. R. Heim, 2007: Effects of temperature and precipitation trends on U.S. drought. *Geophys. Res. Lett.*, **34**, L20709, <https://doi.org/10.1029/2007GL031541>.
- Fatichi, S., V. Y. Ivanov, and E. Caporali, 2012: Investigating interannual variability of precipitation at the global scale: Is there a connection with seasonality? *J. Climate*, **25**, 5512–5523, <https://doi.org/10.1175/JCLI-D-11-00356.1>.
- Feng, S., M. Trnka, M. Hayes, and Y. Zhang, 2017: Why do different drought indices show distinct future drought risk outcomes in the U.S. Great Plains? *J. Climate*, **30**, 265–278, <https://doi.org/10.1175/JCLI-D-15-0590.1>.
- Goodwin, B. K., and V. H. Smith, 2013: What harm is done by subsidizing crop insurance? *Amer. J. Agric. Econ.*, **95**, 489–497, <https://doi.org/10.1093/ajae/aas092>.
- Greatrex, H., J. Hansen, S. Garvin, R. Diro, S. Blakeley, M. Le Guen, K. Rao, and D. Osgood, 2015: Scaling up index insurance for smallholder farmers: Recent evidence and insights. *Climate Change, Agriculture and Food Security Rep.* 14, 32 pp., https://ccafs.cgiar.org/publications/scaling-index-insurance-smallholder-farmers-recent-evidence-and-insights#.XPIb0_4pDcs.

- Guttman, N. B., 1998: Comparing the Palmer drought index and the standardized precipitation index. *J. Amer. Water Resour. Assoc.*, **34**, 113–121, <https://doi.org/10.1111/j.1752-1688.1998.tb05964.x>.
- Hayes, M. J., 2006: Drought indices. *Van Nostrand's Scientific Encyclopedia*, G. D. Considine, Ed., Springer, 11 pp., <https://doi.org/10.1002/0471743984.vse8593>.
- Heim, R. R., 2017: A comparison of the early twenty-first century drought in the United States to the 1930s and 1950s drought episodes. *Bull. Amer. Meteor. Soc.*, **98**, 2579–2592, <https://doi.org/10.1175/BAMS-D-16-0080.1>.
- Heitschmidt, R. K., K. D. Klement, and M. R. Haferkamp, 2005: Interactive effects of drought and grazing on northern Great Plains rangelands. *Rangeland Ecol. Manage.*, **58**, 11–19, [https://doi.org/10.2111/1551-5028\(2005\)58<11:IEODAG>2.0.CO;2](https://doi.org/10.2111/1551-5028(2005)58<11:IEODAG>2.0.CO;2).
- Hoerling, M. P., J. K. Eischeid, X. W. Quan, H. F. Diaz, R. S. Webb, R. M. Dole, and D. R. Easterling, 2012: Is a transition to semipermanent drought conditions imminent in the U.S. Great Plains? *J. Climate*, **25**, 8380–8386, <https://doi.org/10.1175/JCLI-D-12-00449.1>.
- Keyantash, J., and J. A. Dracup, 2002: The qualification of drought: An evaluation of drought indices. *Bull. Amer. Meteor. Soc.*, **83**, 1167–1180, <https://doi.org/10.1175/1520-0477-83.8.1167>.
- Knapp, A. K., C. J. W. Carroll, E. M. Denton, K. J. La Pierre, S. L. Collins, and M. D. Smith, 2015: Differential sensitivity to regional-scale drought in six central US grasslands. *Oecologia*, **177**, 949–957, <https://doi.org/10.1007/s00442-015-3233-6>.
- Knight, T. O., and K. H. Coble, 1997: Survey of U.S. multiple peril crop insurance literature since 1980. *Rev. Agric. Econ.*, **19**, 128–156, <https://doi.org/10.2307/1349683>.
- Leblois, A., and P. Quirion, 2013: Agricultural insurances based on meteorological indices: Realizations, methods and research challenges. *Meteor. Appl.*, **20**, 1–9, <https://doi.org/10.1002/met.303>.
- Lorenz, D. J., J. A. Otkin, M. Svoboda, C. R. Hain, M. C. Anderson, and Y. Zhong, 2017: Predicting U.S. Drought Monitor states using precipitation, soil moisture, and evapotranspiration anomalies. Part I: Development of a nondiscrete USDM index. *J. Hydrometeorol.*, **18**, 1943–1962, <https://doi.org/10.1175/JHM-D-16-0066.1>.
- Maples, J. G., B. W. Brorsen, and J. T. Biermacher, 2016: The rainfall index annual forage pilot program as a risk management tool for cool-season forage. *J. Agric. Appl. Econ.*, **48**, 29–51, <https://doi.org/10.1017/aae.2016.3>.
- McKee, T. B., N. J. Doesken, and J. Kleist, 1993: The relationship of drought frequency and duration to time scales. *Eighth Conf. on Applied Climatology*, Anaheim, CA, Amer. Meteor. Soc., 179–184.
- Miranda, M. J., 1991: Area-yield crop insurance reconsidered. *Amer. J. Agric. Econ.*, **73**, 233–242, <https://doi.org/10.2307/1242708>.
- , and C. Gonzalez-Vega, 2011: Systemic risk, index insurance, and optimal management of agricultural loan portfolios in developing countries. *Amer. J. Agric. Econ.*, **93**, 399–406.
- Moorhead, J. E., P. H. Gowda, V. P. Singh, D. O. Porter, T. H. Marek, T. A. Howell, and B. A. Stewart, 2015: Identifying and evaluating a suitable index for agricultural drought monitoring in the Texas high plains. *J. Amer. Water Resour. Assoc.*, **51**, 807–820, <https://doi.org/10.1111/jawr.12275>.
- Moran, M. S., and Coauthors, 2014: Functional response of U.S. grasslands to the early 21st-century drought. *Ecology*, **95**, 2121–2133, <https://doi.org/10.1890/13-1687.1>.
- Müller, B., M. F. Quaas, K. Frank, and S. Baumgärtner, 2011: Pitfalls and potential of institutional change: Rain-index insurance and the sustainability of rangeland management. *Ecol. Econ.*, **70**, 2137–2144, <https://doi.org/10.1016/j.ecolecon.2011.06.011>.
- Nadolnyak, D., and D. Vedenov, 2013: Information value of climate forecasts for rainfall index insurance for pasture, rangeland, and forage in the southeast United States. *J. Agric. Appl. Econ.*, **45**, 109–124, <https://doi.org/10.1017/S1074070800004612>.
- National Drought Mitigation Center, 2018: United States Drought Monitor. Accessed May 2018, <http://droughtmonitor.unl.edu/Maps/MapArchive.aspx>.
- National Oceanic and Atmospheric Administration, 2017: CPC Unified Gauge-Based Analysis of Daily Precipitation over CONUS. NOAA/Physical Science Division, accessed November 2017, <https://www.esrl.noaa.gov/psd/data/gridded/data.unified.daily.conus.html>.
- Nicholls, N., and K. K. Wong, 1990: Dependence of rainfall variability on mean rainfall, latitude, and the Southern Oscillation. *J. Climate*, **3**, 163–170, [https://doi.org/10.1175/1520-0442\(1990\)003<0163:DORVOM>2.0.CO;2](https://doi.org/10.1175/1520-0442(1990)003<0163:DORVOM>2.0.CO;2).
- Nielsen-Gammon, J. W., 2011: The 2011 Texas drought: A briefing packet for the Texas legislature. 43 pp., <https://oaktrust.library.tamu.edu/handle/1969.1/158245>.
- Palmer, W. C., 1965: Meteorological drought. US Weather Bureau Research Paper 45, 58 pp., <https://www.ncdc.noaa.gov/temp-and-precip/drought/docs/palmer.pdf>.
- Quiring, S. M., and T. N. Papakryiakou, 2003: An evaluation of agricultural drought indices for the Canadian prairies. *Agric. For. Meteorol.*, **118**, 49–62, [https://doi.org/10.1016/S0168-1923\(03\)00072-8](https://doi.org/10.1016/S0168-1923(03)00072-8).
- Reeves, M. C., 2016: Development of the Rangeland Vegetation Simulator: A module of the Forest Vegetation Simulator. Joint Fire Science Program Final Rep. for Projects 12-1-02-15 and 14-S-01-01, 129 pp., http://www.firescience.gov/projects/12-1-02-15/project/12-1-02-15_final_report.pdf.
- Ritter, M., O. Musshoff, and M. Odening, 2014: Minimizing geographical basis risk of weather derivatives using a multi-site rainfall model. *Comput. Econ.*, **44**, 67–86, <https://doi.org/10.1007/s10614-013-9410-y>.
- Sheffield, J., and E. F. Wood, 2008: Projected changes in drought occurrence under future global warming from multi-model, multi-scenario, IPCC AR4 simulations. *Climate Dyn.*, **31**, 79–105, <https://doi.org/10.1007/s00382-007-0340-z>.
- Shrum, T. R., W. R. Travis, T. M. Williams, and E. Lih, 2018: Managing climate risks on the ranch with limited drought information. *Climate Risk Manage.*, **20**, 11–26, <https://doi.org/10.1016/j.crm.2018.01.002>.
- Siebert, A. B., and M. N. Ward, 2011: Future occurrence of threshold-crossing seasonal rainfall totals: Methodology and application to sites in Africa. *J. Appl. Meteor. Climatol.*, **50**, 560–578, <https://doi.org/10.1175/2010JAMC2530.1>.
- Smith, V., and M. Watts, 2009: Index based agricultural insurance in developing countries: Feasibility, scalability and sustainability. Commissioned by the Bill and Melinda Gates Foundation, 40 pp., <https://gatesopenresearch.org/documents/3-65>.
- Svoboda, M., and Coauthors, 2002: The Drought Monitor. *Bull. Amer. Meteor. Soc.*, **83**, 1181–1190, <https://doi.org/10.1175/1520-0477-83.8.1181>.
- U.S. Department of Agriculture, 2017a: Frequently asked questions: Pasture, rangeland, forage. USDA, accessed January 2018, <https://www.rma.usda.gov/News-Room/Frequently-Asked-Questions/Pasture-Rangeland-Forage>.
- , 2017b: Rainfall and vegetation index insurance standards handbook: 2018 and succeeding crop years. USDA Risk Management Agency Federal Crop Insurance Corp. Rep.

- FCIC-18150, 43 pp., <https://www.rma.usda.gov/-/media/RMAweb/Handbooks/Coverage-Plans---18000/Rainfall-and-Vegetation-Index---18150/2018-18150--Rainfall-And-Vegetation-Index-Handbook.ashx?la=en>.
- , 2018a: Actuarial information browser. USDA, accessed February 2018, <https://webapp.rma.usda.gov/apps/actuarialinformationbrowser/>.
- , 2018b: Pasture, rangeland, forage support tool. USDA, accessed May 2018, <https://prodwebnlb.rma.usda.gov/apps/prf>.
- , 2018c: Summary of business reports. USDA, accessed May 2018, <https://www.rma.usda.gov/SummaryOfBusiness>.
- Vedenov, D. V., and B. J. Barnett, 2004: Efficiency of weather derivatives as primary crop insurance instruments. *J. Agric. Resour. Econ.*, **29**, 387–403.
- Vicente-Serrano, S. M., S. Beguería, and J. I. López-Moreno, 2010: A multiscale drought index sensitive to global warming: The standardized precipitation evapotranspiration index. *J. Climate*, **23**, 1696–1718, <https://doi.org/10.1175/2009JCLI2909.1>.
- , and Coauthors, 2012: Performance of drought indices for ecological, agricultural, and hydrological applications. *Earth Interact.*, **16**, <https://doi.org/10.1175/2012EI000434.1>.
- Vroege, W., T. Dalhaus, and R. Finger, 2019: Index insurances for grasslands—A review for Europe and North America. *Agric. Syst.*, **168**, 101–111, <https://doi.org/10.1016/j.agry.2018.10.009>.
- Wells, N., S. Goddard, and M. J. Hayes, 2004: A self-calibrating Palmer drought severity index. *J. Climate*, **17**, 2335–2351, [https://doi.org/10.1175/1520-0442\(2004\)017<2335:ASPSI>2.0.CO;2](https://doi.org/10.1175/1520-0442(2004)017<2335:ASPSI>2.0.CO;2).
- Westerhold, A., C. Walters, K. Brooks, M. Vandever, J. Volesky, and W. Schacht, 2018: Risk implications from the selection of rainfall index insurance intervals. *Agr. Financ. Rev.*, **78**, 514–531, <https://doi.org/10.1108/AFR-10-2017-0097>.
- Winter, J. M., and E. A. B. Eltahir, 2012: Modeling the hydro-climatology of the midwestern United States. Part 2: Future climate. *Climate Dyn.*, **38**, 595–611, <https://doi.org/10.1007/s00382-011-1183-1>.
- Woodard, J. D., and P. Garcia, 2008: Basis risk and weather hedging effectiveness. *Agric. Finance Rev.*, **68**, 99–117, <https://doi.org/10.1108/00214660880001221>.
- Zargar, A., R. Sadiq, B. Naser, and F. I. Khan, 2011: A review of drought indices. *Environ. Rev.*, **19**, 333–349, <https://doi.org/10.1139/a11-013>.