Soil Moisture Information Improves Drought Risk Protection Provided by the USDA Livestock Forage Disaster Program

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ABSTRACT: The USDA Livestock Forage Disaster Program (LFP) offers financial assistance to farmers and ranchers with grazed forage losses caused by fire or drought. Payments for drought losses are based on the U.S. Drought Monitor (USDM), which is designed to integrate meteorological, agricultural, hydrological, ecological, and socioeconomic droughts. Because soil moisture deficit is a more specific measure of agricultural drought, we hypothesized that basing LFP payments on soil moisture observations could better reduce producers’ risk. Therefore, our objectives were to 1) quantify relationships of forage yield with USDM-based LFP payment multipliers and with in situ soil moisture, 2) develop an alternative LFP payment multiplier structure based on in situ soil moisture, and 3) quantify risk reduction using the current and alternative payment structures. We focused on Oklahoma, United States, which has led the nation in LFP payments received and has >25 years of in situ soil moisture observations statewide. Using non-alfalfa hay yield as a surrogate for forage production, we found that LFP payment multiplier values and soil moisture anomaly were each related to yield, and soil moisture anomaly explained 54% of yield variability. However, the USDM-based LFP payment structure sometimes resulted in payments for above-average yield, and higher payments did not always correspond with greater yield losses. We developed an alternative soil-moisture-based payment structure that reduced financial risk by >20% compared with the current USDM-based structure. Our study identifies an improved LFP payment structure for Oklahoma that can be evaluated and refined in other states or nationwide using other soil moisture data sources.

SIGNIFICANCE STATEMENT: The USDA Livestock Forage Disaster Program (LFP) offers financial assistance to farmers and ranchers with grazed forage losses caused by fire or drought, with payment eligibility based on drought severity estimates from the U.S. Drought Monitor (USDM). We hypothesized that the LFP could be improved by instead using soil moisture measurements to trigger payments. We found that forage production in Oklahoma was closely linked to soil moisture, and drought relief payments based on soil moisture measurements increased risk protection compared with those based on the USDM. Our work outlines a method for soil-moisture-based LFP payments in Oklahoma, a state that has led the nation in LFP payments. While challenges remain, this work also provides a framework to develop similar payment structures at the regional and national levels.
1. Introduction
The USDA Livestock Forage Disaster Program (LFP) was introduced with the 2008 U.S. Farm Bill to help farmers and ranchers offset losses of grazed forages caused by fire and drought (MacLachlan et al. 2018), and it is now the largest livestock support program in the United States, with total payments of over $12 billion (in 2022 U.S. dollars) from 2008 to 2022 (Hrozencik et al. 2024). Over this period, farmers and ranchers in Oklahoma, United States, received more LFP funding ($1.4 billion) than those in any other state (Fig. 1). LFP payments for drought-induced losses are based on drought severity estimates from the U.S. Drought Monitor (USDM) (USDA-FSA 2022), a composite drought indicator intended to incorporate meteorological, agricultural, hydrological, ecological, and socioeconomic droughts (Fuchs 2023). However, agricultural drought is specifically linked to soil moisture conditions (Chatterjee et al. 2022), which are key drivers of forage production (Briggs and Knapp 1995; Dahl 1963; Johnston et al. 1969; Krueger et al. 2019, 2021; Torell et al. 2011). Therefore, we hypothesized that the LFP would provide greater risk reduction if it were based on soil moisture observations rather than the USDM. The high payment levels received by Oklahoma farmers, coupled with the availability of long-term soil moisture data across the state, make Oklahoma an ideal location to test this hypothesis.

Introduced in 1999, the USDM has become the most widely used drought indicator in the United States (Brusberg and Shively 2015) and is the “gold standard” for drought monitoring throughout the world (Fuchs 2023). It has been used to trigger drought relief payments since shortly after its introduction (USDA-FSA 2003). The intent of the USDM is to distill drought information from a wide variety of objective and subjective sources into a broadly applicable, easily understandable product that is suitable for use by the general public (Svoboda et al. 2002). It is “an attempt to represent all the different types of drought on one map” (meteorological, agricultural, hydrological, ecological, and socioeconomic), and it encompasses drought time scales that range from daily to multiple years (Fuchs 2023). The USDM classifies drought severity into four major categories (D1, D2, D3, and D4), with a fifth category (D0) depicting abnormally dry conditions. Drought intensity categories are based on dozens of drought indicators, including several that are key: Palmer drought severity index (PDSI), Climate Prediction Center (CPC) modeled soil moisture values, U.S. Geological Survey (USGS) streamflow measurements, standardized precipitation index (SPI), percent of normal precipitation, and remotely sensed vegetation health (Svoboda et al. 2002). As science has advanced, USDM input data have improved, with soil moisture, for example, also now represented by remotely sensed (e.g., NASA GRACE) and modeled soil moisture (e.g., NASA NLDAS2 and CPC Soil Moisture) (NDMC 2023a). These indicators are combined with local reports from more than 450 expert observers around the country, which results in a “convergence of evidence” drought classification. This merging of evidence from a variety of sources is a core principle of the USDM and one of its defining strengths. Weekly USDM maps have now been produced at the national scale for approximately 24 years and are readily available via a dedicated website for use by policymakers, researchers, and the general public.
The USDM is widely used in part because of its ability to integrate multiple types of drought into one composite indicator, but this characteristic may reduce its specificity in representing agricultural drought. Agricultural drought is defined by soil moisture deficits that cause crop yield losses (Wilhite 2000; NDMC 2023b), with crop yield responding to moisture conditions over relatively short time scales (1–3 months) (Peña-Gallardo et al. 2019). Soil moisture fluctuations can be rapid, decreasing from near-maximum plant-available water to critically low levels over only several weeks (Krueger et al. 2017), and the USDM may not fully represent such short-term changes (Christian et al. 2019; Ford et al. 2015). This is logical and inherent in the structure of the USDM because some of the drought indicators used by the USDM vary over longer time scales, with, for example, PDSI representing moisture conditions over a time scale of about 12 months (McKee et al. 1993) and surface and groundwater levels indicating moisture conditions of periods as long as multiple years (Svoboda et al. 2002; Fuchs 2023).

Because the USDM was not specifically optimized to monitor only agricultural drought, it is not expected to be the best predictor of crop yields. For example, growing season temperature...
and precipitation were better predictors of corn ($R^2 = 0.33$) and soybean ($R^2 = 0.29$) yields across the United States than the USDM ($R^2 = 0.15$ for corn and 0.17 for soybean, respectively) (Kuwayama et al. 2018). Likewise, USDM values were less important predictors of forage production than were SPI values in Nebraska, with the USDM sometimes indicating severe drought in years with near-normal grassland productivity (Poděbradská et al. 2019). Another major drought risk management tool, the USDA Pasture, Rangeland, and Forage (PRF) insurance program, bases payments only on precipitation rather than the USDM (USDA-RMA 2021), in part because the USDM uses multiple factors to categorize drought, which makes it difficult to use in insurance systems (Williams and Travis 2019). The PRF still has considerable basis risk (Yu et al. 2019; Cho and Brorsen 2021) and low participation (Goodrich and Davidson 2024), so there is no evidence that payments triggered by precipitation provide better risk reduction than payments triggered by the USDM.

Since soil moisture is the central variable by which agricultural drought is defined (Mishra and Singh 2010), it is not surprising that previous work has found strong relationships between soil moisture and forage production (Briggs and Knapp 1995; Dahl 1963; Johnston et al. 1969; Krueger et al. 2019, 2021; Torell et al. 2011). The conceptual benefits of quantifying agricultural drought using soil moisture make it a logical candidate for LFP payment triggers, but one obstacle that has prevented the use of soil moisture has been the absence of available data. This situation is improving with the proliferation of large-scale soil moisture monitoring networks (Ochsner et al. 2013) and efforts such as the National Coordinated Soil Moisture Monitoring Network (NCSMMN), which seeks to integrate soil moisture data across networks and disseminate nationwide soil moisture data products for the United States (Baker et al. 2022; Cosh et al. 2021). Likewise, the availability and accuracy of satellite-based soil moisture observations have been steadily improving (Babaeian et al. 2019). A second and perhaps larger obstacle is the absence of research relating soil moisture to forage production, drought relief payments, and risk reduction (Abdi et al. 2022). Therefore, our objectives were to 1) quantify the relationships of forage yield with USDM-based LFP payment multipliers and in situ soil moisture data, 2) develop an alternative LFP payment multiplier structure based on measured soil moisture, and 3) quantify risk reduction using the current and alternative payment structures. We used county-level non-alfalfa hay yield data (USDA-NASS 2020a), as a surrogate for forage production, and in situ soil moisture data from the Oklahoma Mesonet, one of the longest-running, large-scale soil moisture networks in the world. Our work outlines a method for soil-moisture-based LFP payments in Oklahoma, and it provides a framework to develop similar regional or national payment structures using other soil moisture data sources.

2. Materials and methods
   a. Study area. The state of Oklahoma is an ideal location to evaluate the LFP payment structure because of the importance of grass and rangelands in the state, the high level of LFP payments the state’s farmers and ranchers have received, and the availability of long-term soil moisture data from the Oklahoma Mesonet. Oklahoma has over 5 million hectares of rangeland, composed primarily of native grasses and other forage plants, and 3 million hectares of pasture, consisting primarily of introduced forages (USDA-NRCS 2015). Together, grasslands and rangelands account for nearly 50% of the state’s land cover (USDA-NASS 2020b) (Fig. 2). Bermuda grass is the most common introduced forage in Oklahoma, covering approximately 1.6 million hectares, with other perennial warm-season forages such as Old World bluestem, weeping love grass, and bahia grass each generally grown on less than 200 000 ha (Redfearn and Caddel 2006). Introduced cool-season forages are far less common in Oklahoma, with tall fescue being the most important perennial species and annual ryegrass being the most important annual species, each covering approximately 400 000 ha (Redfearn and Caddel 2006). Winter wheat is commonly planted on cropland across the
state and is often used for grazing as well. Predominant vegetation varies as a function of precipitation and temperature across Oklahoma, with grassland being common in the westernmost third of the state, cultivated crops and grasslands being common in the central third, and grasslands and deciduous forests being common across the eastern third (Fig. 2). Oklahoma’s grass and rangelands support its beef cattle industry, which consisted of more than 2 million beef cows in 2017, ranking third in the United States, and cattle sales of more than $3.2 billion (U.S. dollars) in 2019 (USDA-NASS 2020a).

b. LFP. The LFP was created by the 2008 U.S. Farm Bill (Food, Conservation, and Energy Act of 2008 P.L. 110–234 H.R. 2419) as a means of offering financial assistance to farmers and ranchers that suffered forage losses due to drought or fire on grazing lands. The 2008 Farm Bill covered losses from 1 January 2008 until 1 October 2011, and the LFP was continued by the 2014 and 2018 Farm Bills (Agricultural Act of 2014 P.L. 113–79 H.R. 2642 and Agricultural Improvement Act of 2018 P.L. 115–334 H.R. 2), with the 2014 Farm Bill providing retroactive payments back to 1 October 2011. The program is aimed at farmers and ranchers with livestock that meet the majority of their energy requirements through grazing, with animals covered by the LFP including beef and dairy cattle, alpacas, buffalo/bison, beefalo, deer, elk, emus, equine, goats, llamas, reindeer, and sheep (USDA-FSA 2022).

For drought-induced losses, annual LFP payments depend on county-level values of 1) the monthly payment rate and 2) the monthly payment multiplier (USDA-FSA 2018). The monthly payment rate is an estimate of the monthly cost of supplemental feed for livestock, and the monthly payment multiplier represents the number of months over which supplemental feed is necessary. The monthly payment rate varies by livestock class and is determined annually by the Farm Service Agency (FSA). It is calculated as the lesser of the monthly feed cost for (i) all covered livestock owned or leased by the eligible livestock producer or (ii) calculated using the normal carrying capacity of the eligible grazing land. The monthly payment multiplier is based on the U.S. Drought Monitor (USDA-FSA 2022), with payments increasing as drought increases through categories D2 (severe drought), D3 (extreme drought), and D4 (exceptional drought) (Table 1). While the weekly USDM map includes drought subcategories of short-, long-, and short- and long-term drought, these subcategories are not considered by the LFP.
and therefore were not considered in our analysis. Eligible livestock producers must show evidence of loss and have animals that were or would have been grazing during the “normal grazing period” (USDA-FSA 2018), which is defined by the FSA and varies by forage type and county (Table 2). After determining the monthly payment rate and monthly payment multiplier, the annual LFP payment is calculated as

\[
P_{\text{USDM}} = \text{monthly payment rate} \times \text{payment multiplier} \times 0.6,
\]

where \(P_{\text{USDM}}\) is the total payment ($ per head) and the factor of 0.60 is included because the program is designed to pay 60% of the cost for supplemental feed required to compensate for drought-induced grazed forage losses. For example, consider a farmer or rancher with an eligible herd of adult beef cows, which in 2022 had a payment rate of $47.29 per head (USDA-FSA 2022), in a county that experienced 4 weeks of exceptional drought, i.e., D4, resulting in a payment multiplier of 5. This individual would be eligible for a payment of $47.29 per head per month × 5 months × 0.6 = $94.14 per head.

c. Soil moisture. In situ soil moisture data measured under grassland vegetation were obtained from the Oklahoma Mesonet for 2000–2018. This period was chosen because it spans the period when both soil moisture and county hay yield data were available. The collection of annual county hay yield data in Oklahoma was discontinued by the USDA in 2018. With measurements at more than 100 locations (McPherson et al. 2007) spanning over 180,000 km\(^2\) (Fig. 2), the Oklahoma Mesonet is one of the most densely monitored,
large-scale soil moisture networks in the world (Ochsner et al. 2013). Data were received as half-hourly reference temperature difference measured using heat dissipation sensors (Model 229; Campbell Scientific Inc., Logan, Utah, United States) (Iillston et al. 2008). Half-hourly data were averaged each day and then used to determine daily matric potential (Zhang et al. 2019), which in turn was used to calculate volumetric soil water content $\theta$ based on estimated soil water retention parameters (Wyatt et al. 2021), which was then used to estimate the fraction of available water capacity (FAW). Daily matric potential values were calculated using the logistic equation described by Zhang et al. (2019). These matric potentials were then converted to volumetric water content $\theta$ using the van Genuchten soil water retention equation (van Genuchten 1980). The parameters of the van Genuchten equation for each Mesonet site and sensor depth were taken from the MesoSoil database (Scott et al. 2013) as updated by Wyatt et al. (2021). The $\theta$ values were then converted to FAW, which was calculated as

$$FAW = \frac{(\theta - \theta_{wp})}{(\theta_{fc} - \theta_{wp})},$$  

where $\theta_{wp}$ is the volumetric water content at the permanent wilting point and $\theta_{fc}$ is the volumetric water content at field capacity (Krueger et al. 2019). FAW has a range of approximately 0–1, with 0 representing no plant-available water and 1 representing maximum plant-available water. Permanent wilting point was defined as the volumetric water content corresponding to a matric potential of $-1500$ kPa, and field capacity was defined as the volumetric water content corresponding to a matric potential of $-10$ kPa. These matric potential values were inserted into the van Genuchten soil water retention equation, along with site- and depth-specific van Genuchten parameters, to estimate volumetric water content values at the permanent wilting point and field capacity for each site and depth. FAW was determined across a soil depth of 0–40 cm by calculating the depth-weighted average of FAW recorded at the 5- and 25-cm soil depths. Data recorded at 5-cm depth (the midpoint of the 0–10-cm layer) were weighted as 0.25 and data recorded at the 25-cm depth (the midpoint of the 10–40-cm layer) were weighted as 0.75 for the determination of the depth-weighted average. The 0–40-cm depth was chosen because it covers most of the effective rooting depth in grasslands (Jackson et al. 1996; Yang et al. 2016) and because only 76 Oklahoma Mesonet sites record soil moisture at deeper depths (McPherson et al. 2007).

FAW for each county was calculated by averaging values from the five Oklahoma Mesonet stations nearest the geographic center of each county. This spatial averaging technique was chosen to partially offset inaccuracies that can occur by applying point measurements of soil moisture to large spatial areas. The county-level FAW anomaly was then calculated for each day of the year by subtracting the long-term average FAW (2000–18) for that day of the year from the observed daily values. To represent average soil moisture conditions during the growing season, these daily county-level FAW anomaly data were averaged across the period of significant soil moisture–hay yield correlation, approximately 30 May–10 August (Krueger et al. 2019), and this average was used for all subsequent analyses.

d. Hay yield. Our analyses compared the relationships of LFP payment multiplier values and measured FAW anomaly with forage production, where hay yield data were used to represent forage production. The National Agricultural Statistics Service provided hay yield estimates annually through the Agricultural Survey until 2018. These data are separated only by alfalfa and non-alfalfa hay types, with the latter including data from wild hay, small grain hay, and other tame hay types. On the other hand, the Census of Agriculture (USDA-NASS 2020a), while only available every 5 years (2002, 2007, and 2012 in our study), provides separate yield values for each hay type (alfalfa, wild, small grain, and tame). Data for wild
and tame hay were not recorded in the 2017 Census of Agriculture. The Census of Agriculture data were used to select counties for our analysis, and Agricultural Survey data were used for statistical analyses on selected counties.

Given the predominance of grasslands in Oklahoma, we focused on native pasture and improved warm-season pasture types, each with a normal grazing period of 15 April–14 November for most counties (Table 2). Data from the 2002, 2007, and 2012 Censuses of Agriculture were used to identify counties that primarily grow wild and tame hay (hay types that exclude alfalfa and small grain hay). We identified 30 counties with a wild and tame hay area of at least 25,000 ha (average of 44,000 ha) and at least 90% (average of 96%) of total non-alfalfa hay production from wild and tame hay types. The resulting dataset consisted of 449 hay yield values, which is less than the maximum possible number of data points (30 counties × 19 years = 570) because yields were not reported for some counties in some years. Statistical analyses were performed on hay yield anomaly values, which were calculated by subtracting long-term county-average yield from annual yield data. We did not account for any potential impacts of irrigation on county-level hay yields because irrigated area accounted for only 1.4% of total wild and tame hay production in Oklahoma when averaged across Census of Agriculture years (USDA-NASS 2020a).

e. Statistical analysis. Yield anomaly values for each payment multiplier category were displayed using box-and-whisker plots that represented the 25th, 50th (median), and 75th percentile values of hay yield for a given category of each drought indicator. Whisker length was calculated as 1.5 times the interquartile range, and outliers were displayed as individual points (Frigge et al. 1989). The notches on each box were calculated as the 95% confidence interval on the median values as

\[
M \pm 1.57 \left( \frac{R}{\sqrt{n}} \right),
\]

where \( M \) is the median, \( R \) is the interquartile range, and \( n \) is the number of samples (McGill et al. 1978). The null hypotheses of no differences in county-level mean hay yield anomalies between payment multiplier categories were tested using analysis of variance. The test was performed for payment multipliers from both the current USDM-based system (Table 1) and the alternative FAW-anomaly-based system. Post hoc multiple comparisons of yield anomaly values were then performed using the Tukey–Kramer method. Significant differences between categories were indicated by lowercase letters above each box-and-whisker plot.

While the LFP payment multiplier value is a categorical variable, FAW anomaly is continuous, which allowed for more diverse statistical techniques. For example, simple linear regression analyses of county-level hay yield anomaly and FAW anomaly corroborated previous work reporting strong relationships between soil moisture and hay yield (Krueger et al. 2019, 2021). However, a visual inspection of the corresponding yield anomaly–FAW anomaly scatterplot suggested that a piecewise regression may be more appropriate for these data than simple linear regression. Therefore, data were analyzed using a piecewise regression equation of the following form (Ryan and Porth 2007):

\[
yield_{ct} = \begin{cases} 
  m_1 \text{FAWanomaly}_{ct} + b_1 & \text{for } \text{FAWanomaly}_{ct} \leq c \\
  m_2 \text{FAWanomaly}_{ct} + c(m_1 - m_2) + b_1 & \text{for } \text{FAWanomaly}_{ct} > c
\end{cases},
\]

where \( \text{yield}_{ct} \) is hay yield anomaly for county \( c \) and year \( t \), \( \text{FAWanomaly} \) is the average from 30 May through 10 August, \( m_1 \) and \( m_2 \) are the slopes of the lower and upper segments,
respectively, $b_1$ is the intercept of the lower segment, and $c$ is the breakpoint between segments. Data were fit using the “fitnlm” function in MATLAB R2018a, which uses the Levenberg–Marquardt nonlinear least squares algorithm (Seber and Wild 2003), and regression performance was assessed using the coefficient of determination $r^2$. We used the results of this analysis to help define an alternative FAW-based LFP payment structure with FAW anomaly categories defined as $FAW$ anomaly $< -0.35$ for a payment multiplier of 5, $-0.35 \leq FAW$ anomaly $< -0.25$ for a payment multiplier of 3, and $-0.25 \leq FAW$ anomaly $< -0.10$ for a payment multiplier of 1.

**f. Risk measure.** The LFP and the Pasture, Range, and Forage (PRF) crop insurance programs are similar in that they are both designed to protect against forage losses. The PRF and a similar program for annual forage (Rainfall Index Annual Forage Program) have been researched extensively (Cho and Brorsen 2021; Coble et al. 2020; Keller and Saitone 2022; Williams and Travis 2019). Some of this literature measured risk as the probability of not receiving payment when there was a loss (i.e., occurrence of false negatives) (Keller and Saitone 2022; Yu et al. 2019), while other research used mean–variance or mean–semivariance (Cho and Brorsen 2021; Shalek-Briski et al. 2021; Westerhold et al. 2018). We evaluated both types of measures, although rather than semivariance we used target deviations based on Fishburn (1977). We defined false negatives as occurring when actual revenue was less than 85% of the expected revenue and no payment was made. A justification for this 85% threshold is that the median coverage level selected by producers in 2022 for the Pasture, Range, and Forage crop insurance program was 85% (USDA-RMA 2023).

The target deviation risk measure was calculated as

$$D = \sum_c \sum_t \max\left[\pi_{ct} - \left(\pi_{ct} + P\right), 0\right]/N,$$

where $D$ is the target deviation ($\$/head/year) without LFP payment, $\pi$ is the expected annual revenue ($\$/head) without LFP payment, $\rho$ is the percent of average revenue that is selected as the target, $\pi_{ct}$ is the actual annual revenue ($\$/head) without payment for county $c$ and year $t$, $P$ is revenue from LFP payments ($\$/head), and $N$ is the total number of observations across counties and years. As with the false-negative risk measure, we used a threshold value of $\rho = 0.85$, so the risk measure is the average of the deviations of the actual annual revenue below 85% of the expected annual revenue without payment. Note that the LFP seeks to pay 60% of the extra forage costs due to drought. The 60% is what Cho and Brorsen (2021) call a hedge ratio and is unconnected to the 85% target of the utility function.

To estimate expected revenue $\pi$ for the 7-month grazing period, we assumed that the value of 1 month of grazing was equal to the monthly payment rate for one beef cow provided by the LFP ($47.29 per head per month). So the expected revenue (i.e., forage value) was 7 months $\times$ $47.29 per head per month $= 331.03 per head. The actual revenue $\pi_{ct}$ from grazing was computed as

$$\pi_{ct} = 331.03 \text{ per head} \times \frac{\text{yield}_{ct}}{\text{yield}_{c}},$$

where $\text{yield}_{ct}$ is the yield for county $c$ in year $t$ and $\text{yield}_{c}$ is the average yield for county $c$. Finally, payments for the FAW-anomaly-based payment structure $P$ were calculated similarly to the USDM-based payment structure [Eq. (1)] as

$$P_{FAW\text{anomaly}} = 47.29 \text{ per head per month} \times \text{payment multiplier}_{\pi_{ct}} \times 0.6 \times \text{rating},$$
where the payment multiplier is determined for each county \( c \) and year \( t \) based on drought conditions (Table 3). “Rating” is the ratio of total payment multipliers in the USDM-based and FAW-anomaly-based LFP payment structures, and it was included so the total dollar amount of payments was the same under the current and the proposed programs. The rating value was 1.15. Using this series of equations, the target deviation risk measure \( D \) was calculated for the current USDM-based LFP system and for an alternative FAW-anomaly-based system, with lower values of \( D \) representing a reduction in risk experienced by farmers and ranchers.

3. Results and discussion

a. Relating the LFP and USDM to hay yield. While payments totaling billions of dollars have been made through the LFP since its inception in 2008, research linking these payments to actual forage yields is lacking. Box-and-whisker plots (Fig. 3) relating payment multipliers with hay yield show that the USDM-based payment multipliers were generally higher when yields were lower (Fig. 3). Years when no LFP payment was made [USDM values of no drought (none), abnormally dry conditions (D0), and moderate drought (D1)] usually corresponded with above-average yield. However, the USDM-based payment structure displayed two undesirable features. First, payments associated with a payment multiplier = 1 were often unwarranted because the average hay yield anomaly was positive under these conditions. These payments were triggered by eight consecutive weeks of severe drought (D2) during the normal grazing period. County-level hay yields were above average 66% of the time when a payment multiplier of 1 occurred in our dataset. Second, yields were not significantly different between payment multipliers 3 and 4 (Fig. 3), indicating that the USDM-based payment structure often assigned different payment levels to county–year combinations experiencing similar drought impacts on forage production. Because the USDM has been continually improved since its inception, we also considered more recent periods of record (2011–18 and 2014–18). We found similar results regardless of the chosen period of record, and the shorter time periods were not used further due to their smaller sample sizes.

b. Relating in situ soil moisture to hay yield. These mismatches between payment levels and drought impacts on forage yield may occur because the USDM, which is the basis of LFP payments, represents the combined effects of all types of drought rather than agricultural drought alone (Fuchs 2023). Soil moisture conditions, on the other hand, provide a more specific measure of agricultural drought and so may be a better predictor of forage yield. A regression of non-alfalfa hay yield against soil moisture, represented as average FAW anomaly from 30 May to 10 August (Krueger et al. 2019), accounted for 54% of the
variability in yield (Fig. 4a). A break in the relationship occurred at FAW anomaly = −0.11, below which yield decreased sharply at a rate of 472 kg ha\(^{-1}\) for each 0.1 decrease in FAW anomaly. Above this threshold, yield decreased by 130 kg ha\(^{-1}\) for each 0.1 decrease in FAW anomaly. The piecewise regression equation predicts below average yield (negative anomaly) below a threshold FAW anomaly value of −0.12, indicating that average yields may be attained even when soil moisture is slightly below average.

To create an alternative LFP payment multiplier structure based on measured soil moisture, we categorized FAW anomaly values in a form similar to the current system (Fig. 4b), with categories informed by findings from the regression analysis (Fig. 4a). First, FAW anomaly was subdivided by values that approximately corresponded with above-average yield (FAW anomaly ≥ −0.10) and below-average yield (FAW anomaly < −0.10). Next, FAW anomalies associated with below-average yield were subdivided as −0.25 ≤ FAW anomaly < −0.10 (payment multiplier 1), −0.35 ≤ FAW anomaly < −0.25 (payment multiplier 3), and FAW anomaly < −0.35 (payment multiplier 5) (Table 3). These divisions represent negative anomalies in soil water storage exceeding 10%, 25%, and 35% of the soil’s plant-available water capacity, respectively.

Using these categories, the soil-moisture-based payment structure outperformed the USDM-based payment structure. Increasing payment multiplier values was associated with decreased yield (Fig. 4b), and unlike the USDM-based system, the average yield anomaly was negative for a payment multiplier = 1, as it should be. As a result, fewer soil-moisture-based payments were associated with above-average yields, with only 18 of 457 payment multipliers (4%) occurring when the yield was above average. Conversely, 60 of 501 payment multipliers (12%) for the USDM-based system occurred when the yield was above average. Furthermore, unlike for the USDM-based system, a multiplier value of 1 occurred more frequently than for...
other values (Table 3), which is logical since mild droughts occur more frequently than severe
droughts (Svoboda et al. 2002). Also, statistically significant differences in yield anomaly
existed between all payment multiplier categories for the soil-moisture-based system, in-
dicating this structure provided better differentiation of drought impact levels than did the
USDM-based payment structure. These results indicate good potential for using soil moisture
measurements to target drought relief payments.

c. Risk reduction with a FAW-anomaly-based payment structure. Because forage yields
were more closely linked to soil moisture than to the USDM-based LFP payment structure, the

Fig. 4. (a) Scatterplot and (b) box-and-whisker plot of FAW anomaly and non-alfalfa hay yield anomaly
from 2000 to 2018. Hay yield anomaly data are for the 30 top wild and tame hay producing counties in
the state, and FAW anomaly is the county-level average from 30 May to 10 Aug. Different lowercase
letters in (b) indicate significant differences at $p \leq 0.05$. While yield was related to soil moisture across
the entire range of FAW anomaly values, yield anomaly was negative and declined sharply as FAW
anomaly declined below approximately −0.11. The boxplots are presented as a potential alternative
LFP payment multiplier structure.
payment structure based on FAW anomalies could provide a more objective basis for payments and greater risk reduction for farmers and ranchers. We used two measures of risk to assess the performance of the soil-moisture-based payment structure. First, we quantified the probability of not receiving a payment when there was a loss (i.e., probability of a false negative) under the USDM-based and FAW-anomaly-based payment structures. Both systems greatly reduced the potential for loss without payment relative to having no protection program, but the FAW-anomaly-based payment structure provided 23% fewer occurrences of losses (i.e., revenue < 85% of average) without payment than the USDM-based payment structure (Table 4). Next, we used the target deviation risk measure $D$ to quantify risk under each system and found that, for the FAW-anomaly-based payment structure, the risk was reduced by 24% compared with the USDM-based payment structure (Table 4). Collectively, these results are evidence that the soil-moisture-based categories and multiplier values better represent actual forage losses in Oklahoma than the current USDM-based payment structure.

d. Implications for drought relief payments. When the USDM was first used to assign disaster relief payments in 2003 and later as the basis for LFP payments in 2008, large-scale soil moisture monitoring networks were not as well established as they are currently (Cosh et al. 2021). Now, the situation is changing, with in situ soil moisture measurement networks spanning much of the United States (Cosh et al. 2021) and continual improvements in the coverage, resolution, and accuracy of remotely sensed soil moisture data (Ford and Quiring 2019). Our results show that soil moisture data can provide a more objective and effective basis for assigning LFP disaster relief payments than the current USDM-based payment structure, at least in Oklahoma. This does not reflect an inherent flaw in the USDM, but rather the fact that the USDM was not designed to quantify agricultural drought specifically. The USDM was designed as an easily understandable drought indicator capable of simultaneously representing multiple types of drought that occur over multiple time scales (Svoboda et al. 2002; Fuchs 2023). Some drought conditions (e.g., hydrologic drought) represented by the USDM have little direct impact on the production of grazed forage. Thus, it is logical that measurements of soil moisture, the fundamental variable by which agricultural drought is defined (NDMC 2023b), may be better suited to assigning LFP payments than the USDM. This same reasoning also limits the usefulness of the USDM in single-peril insurance programs like the Pasture, Rangeland, and Insurance program (USDA-RMA 2021) and similar programs around the world (Vroege et al. 2019). Quantitative and continuous water deficiency indices such as FAW anomaly do not suffer from this limitation (Williams and Travis 2019) and may, therefore, help fill the need for new and improved indices for agriculture insurance (Leblois and Quirion 2013).

Table 4. Payments, losses without payments, and target deviation risk measure $D$ for the USDM- and FAW-anomaly-based payment structures. Data are for the top 30 wild and tame hay producing counties in Oklahoma from 2000 to 2018. Each program was effective at reducing risk to farmers and ranchers, but the FAW-anomaly-based payment structure provided a 23%–24% improvement over the USDM-based payment structure. Note: Alternatives to the 85% threshold were considered. Alternatives to the payment categories used for FAW anomaly were also considered. The main finding of FAW anomaly being more effective in reducing risk than the USDM did not change with these changes.

<table>
<thead>
<tr>
<th>Measure</th>
<th>No program</th>
<th>USDM</th>
<th>FAW anomaly</th>
<th>Risk reduction using FAW anomaly</th>
</tr>
</thead>
<tbody>
<tr>
<td>Payments ($ per head) (USDA-FSA 2022)</td>
<td>0</td>
<td>$47.29</td>
<td>$47.29</td>
<td>—</td>
</tr>
<tr>
<td>Loss without payments</td>
<td>23%</td>
<td>7.8%</td>
<td>6.0%</td>
<td>23%</td>
</tr>
<tr>
<td>Target deviation risk measure ($ per head per year) $D$</td>
<td>12.8</td>
<td>2.07</td>
<td>1.57</td>
<td>24%</td>
</tr>
</tbody>
</table>

* Probability of a false negative, or the percent of time that revenues were less than 85% of the county average and no payment was made.
* The target deviations are calculated as the sum of all deviations of returns less than 85% of the county mean.
These results in Oklahoma highlight a need for further research to evaluate the potential for developing a nationwide LFP payment structure that more accurately represents the impacts of drought on forage production. In the meantime, some improvements to the current payment structure may be possible by simple policy adjustments. First, while a detailed analysis was beyond the scope of our study, eliminating payments for D2 drought categories may avoid payments for above-average yield, which appears to be one of the primary flaws with the current system. Second, research has shown that available soil moisture during early summer is most critical for warm-season hay production, but with the current system, drought conditions anytime from 15 April through 14 November can trigger relief payments on native and warm-season improved pasture in Oklahoma. The performance of the current system might be improved by prioritizing drought conditions that occur during the times of peak forage growth, rather than the entire grazing season. Third, individual components of the USDM, such as the experimental “short-term blend,” may be evaluated for potential use as the basis of LFP payments. Fourth, an assessment of multiplier values relative to actual forage yield is essential to more accurately assign payment multipliers under the current system. These potential improvements are at this stage merely speculative and require further study.

4. Remaining challenges and a way forward

While the soil-moisture-based payment structure developed here is one promising alternative to the current USDM-based approach, at least two key roadblocks hinder its implementation across the United States: 1) inadequate in situ soil moisture monitoring at the national level and 2) the logistical challenges that would be associated with transitioning to a soil-moisture-based payment structure. Overcoming these obstacles will require the cooperation of the diverse stakeholder groups that are impacted by the LFP, and several key research questions remain: “How can FAW anomaly be determined in areas where soil properties are not known?”; “What spatial density of soil moisture monitoring is needed?”; “What FAW anomaly categories should be used outside the state of Oklahoma and for other forage types?”; “Over what period during the growing season is soil moisture most important for other forages and locations?”; “How might information regarding vegetation conditions be coupled with soil moisture data to further improve payment distribution?”; and “How can remotely sensed or modeled soil moisture be used to develop effective payment structures where in situ data are insufficient?”. Answering these questions may further improve LFP payment distribution.

Research advancements on this front may be aided by the continued development of the National Coordinated Soil Moisture Monitoring Network, which is currently working to compile and disseminate soil moisture data from existing monitoring networks and has developed a roadmap for expanding in situ soil moisture observations nationwide (NCSMMN 2023). Improved soil moisture monitoring through this effort could have a multitude of positive impacts, some of which may apply directly to the LFP, for example, by improving the USDM’s convergence of evidence approach in areas where soil moisture measurements are currently lacking. Improved soil moisture monitoring may also be useful to develop stand-alone drought assessments, or they may be incorporated into existing drought metrics, which until now have underused in situ soil moisture data. As this science continues to develop, policymakers should consider incorporating soil moisture information into the LFP payment structure to ensure a more equitable distribution of relief payments. Policymakers should also invest in expanding and maintaining the nation’s soil moisture monitoring infrastructure. These changes will require the farmers and ranchers that depend on the LFP to reevaluate the way in which they understand and interpret drought measures. Our work represents a first step toward improving how these important drought relief payments are distributed, and it is up to scientists, policymakers, farmers, and ranchers to work together to drive the necessary follow-up research to ultimately guide improved policy at the national level.
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Data availability statement. All data used for this work are freely available to the public. Raw soil moisture data are available through the daily data retrieval web page of the Oklahoma Mesonet (https://www.mesonet.org/index.php/past_data/daily_data_retrieval). The soil physical parameter database (MesoSoil v. 2.0) used to convert raw soil moisture data to FAW is available from the Department of Plant and Soil Sciences at Oklahoma State University (http://soilphysics.okstate.edu/data/). LFP payment data were obtained from the Stillwater, Oklahoma Office of the USDA Farm Service Agency. Hay yield data from the USDA Census of Agriculture and the USDA Survey of Agriculture were obtained from the National Agriculture Statistics Service (https://www.nass.usda.gov).
References


