How Drought Shocks Alfalfa Production and Export? Evidence from U.S. Alfalfa Spatial Diagnostics and Panel Evidence

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Abstract

Drought threatens the stability of the United States' forage system, yet the magnitude and spatial heterogeneity of its impacts on alfalfa remain poorly quantified. Using a state-level panel that links the SPEI, alfalfa yield, export, and integrates geospatial diagnostics with panel econometric models. We find that drought reduces yields, with the largest contractions in irrigated Western states. However, production capacity is also shaped by export incentives, spatial/logistical advantages, and water regulations that can partially buffer drought impacts and sustain irrigation-intensive systems. Spatial diagnostics show near-zero cross-covariance between SPEI and export value, but both variables show significant spatial autocorrelation independently. Our findings underscore the need for region-specific adaptation strategies for irrigation water efficiency and acreage management in the West, and feed supply risk tools in the Midwest to maintain forage availability and resilience under intensifying drought stress.

Keywords: Alfalfa, Geo-computation, Drought, Spatial analysis

Introduction

Drought can contribute to altered rates of carbon, nutrient, and water cycling—all of which can impact agricultural food systems[1], critical ecosystem functions that underpin agricultural systems, and the livelihoods and health of farming communities (Burt et al., 2025; Worley et al., 2024). As shown in table 1, National Oceanic and Atmospheric Administration (NOAA) - National Integrated Drought Information System (NIDIS) estimation illustrated that drought impacted roughly one third of alfalfa acreage and relevant industries in 2025 in the United States, underscoring alfalfa's exposure to water stress and the vulnerability of dairy and meat feed supply chains that depend on it.

Table 1: Agriculture affected by drought

Source: NOAA-NIDIS, updated in Oct. 2025.

Commodity	% Area Affected
Alfalfa Hay Acreage	32
Hay Inventory	33
Milk Cow Inventory	39
Cattle Inventory	25

Climate extremes like the multi-year Western drought have curtailed alfalfa hay output (from 2017 to now), a critical feed for dairy cows. Western states such as California, Arizona, and Washington traditionally rely on irrigation and export a significant share of their alfalfa (about 20% of alfalfa hay produced in the West is exported) (Sall et al., 2023). The upper Midwest (e.g., Wisconsin, Minnesota), where alfalfa is largely rain-fed, integrated into local dairy farm operations, and produced for domestic use. This regional distinction — western hay markets influenced by export demand and Midwest production geared toward on farm feed — has been highlighted in USDA's 2023 Alfalfa Outlook (USDA,2023). The feed output is expected to be sustained, as gains in forage yields offset anticipated declines in corn grain yields. Lobell and Villoria (2023) and Tucker et al. (2024) indicated that domestic agricultural adaptations to climate change can shift production abroad, highlighting the importance of a global perspective on trade and land use. Similarly, Villoria et al. (2024) shows that trade policy plays a crucial role in buffering climate shocks: in a structural gravity simulation of El Niño, eliminating trade frictions significantly dampened food price spikes by enabling imports. Besides, flexible

[1] Food products refer to a wide range of products such as animal feed, meat and its preparation, milled grain products, foodstuffs, beverages, and tobacco products.

water regulations and intensive irrigation can buffer drought impacts on production (Cantor et al., 2022). These studies suggest that climate shocks, irrigation practices and trade condition are deeply connected to economic outcomes in agriculture.

Figure 1 shows the average acres of alfalfa of each state over the past 20 years. Alfalfa acreage peaked in the early 2000s and has declined in many areas, partly reflecting water limitations and competition from other crops. Lobell and Villoria (2023) indicated that reducing crop productivity through stress or conservation measures can have spillovers – a 5% drop in farm yield can erode 70–80% of the net climate benefit of a practice once global change in land use is considered. Cantor et al. (2022) argue that alfalfa delivers comparatively low water use efficiency and economic returns per unit of water ("dollars per drop" and "jobs per drop"). They characterize alfalfa as a low value, water intensive forage whose principal role is as an core input into dairy and meat production systems. However, Fleck (2016) argue that alfalfa can enhance system resiliency because it is relatively "flexible": producers can readily idle (fallow) stands or reduce irrigation when water becomes scarce, making alfalfa a manageable margin of adjustment during drought. Overall, the background evidence suggests that drought impacts on alfalfa production and export are nationally important issues that spans biophysical and economic domains. Economic discussion of alfalfa is often led by agronomy and water management studies, with comparatively less work from agricultural economists on export and drought (Montazar et al., 2017; Putnam & Meccage, 2022). Given that context, this paper integrates spatial drought diagnostics with econometric modeling to quantify how drought affects alfalfa yields, acreage, and exports, and to assess whether irrigation and international trade by spatial location—buffer these impacts.

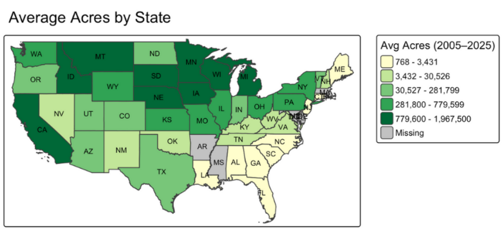

Figure 1: Alfalfa average annual acreage
Source: USDA-NASS

Background

Alfalfa is the third most valuable field crop nationally (about 23 million acres harvested, worth $9 billion annually) and is paradoxically both drought tolerant biologically and water intensive agronomically (Undersander, 2021; USDA-ARS, n.d.). Its deep root system (2–6 m) helps the plant survive rain deficits, but achieving high yields with multiple cuttings per year typically requires substantial irrigation. In figure 2 and appendix figure A.15 indicate alfalfa export rate (the percentage of production that is exported). About 50% of export forage is alfalfa in U.S. and more than 20% alfalfa hay production is shipped overseas in the Western states (Arizona, California, Idaho, Nevada, Oregon, Utah and Washington) (Feuz & Larsen, 2023; Sall et al., 2023). California Department of Water Resources–based estimates indicate that alfalfa irrigation uses roughly 15% of California's agricultural water, making alfalfa the single largest crop in statewide net agricultural water use, which creating an export oriented, water dependent production system in that region (Borton et al., 1997; Cantor et al., 2022; Putnam & Meccage, 2022). In contrast, the Upper Midwest (e.g. Wisconsin, Minnesota) grows alfalfa largely rain-fed and for on farm use in local dairy operations. This regional distinction a water limited (export driven West versus a rain-fed), domestically focused Midwest has been highlighted in USDA's 2023 Alfalfa Outlook and other studies.

Figure 2: State level alfalfa export rate
Data source: USDA NASS and USDA GATS

Alfalfa is central to water debates in the West. A new modeling analysis argues summer deficit irrigation can save 16–50% of alfalfa water with limited on field economic losses and potential net gains when conserved water is tradable (Waring et al., 2025). When surface supplies dwindle, western farmers turn to groundwater as a backup. Western states allocate water under the prior appropriation doctrine (first-in-time, first-in-right), which means senior water rights holders often continue irrigation in drought period (Watch, 2025). Besides, the beneficial-use ("use-it-or-lose-it") doctrine can discourage water right holders from reducing diversions, sustaining irrigation of water intensive alfalfa to preserve legal claims (Cantor, 2021; Cantor et al., 2022). When surface supplies dwindle, western farmers usually turn to groundwater as a backup to keep crops alive

(Watch, 2025). State level export accounting shows sizable hay movements from water scarce states and provides first cut “embodied water” estimates tied to exports (Sall et al., 2023). Njuki (2022) document robust total factor productivity (TFP) growth in large herd Western states, alongside slower gains among smaller herds and organic operations, highlighting an ongoing structural shift toward greater scale and regional concentration. There is no peer reviewed studies specifically addressed alfalfa export under drought; much of the “exporting water” (virtual water) discussion instead appears in policy commentary and journalism, particularly around exports of irrigated hay from the U.S. West to water scarce importing regions (Ben Jervey, 2014).

Liu et al. (2018) indicated severe drought stress reduces alfalfa biomass and yields, whereas moderate deficit irrigation can sometimes improve water use efficiency with comparatively small yield penalties. Economic analyses of drought impacts in alfalfa markets are emerging but remain relatively sparse, often emphasizing price formation and market adjustments rather than production, export and stakeholder response (Ardakani, 2025; Rowley, 2023). More interdisciplinary studies are needed to quantify alfalfa export relationship with drought and spatial characteristic. This paper studies the impacts of drought on United States alfalfa production, and explores spatial relative patterns using geo-computation methods. Figure 3 tracks changes in irrigated alfalfa area by state, reflecting how water availability has been forcing adjustments in crop area. Notably, some traditionally irrigated western states like California, Arizona, and Nevada show declines in alfalfa acreage under irrigation in recent years, likely due to water scarcity and shifting crop priorities.

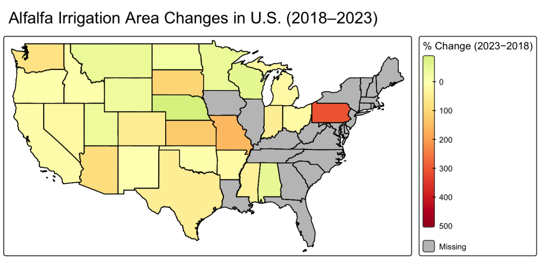

Figure 3: Alfalfa irrigation area changes

Notes: Changes in irrigated alfalfa harvested area by state (2018–2023). Orange and red shading denotes states with major acreage declines under irrigation (e.g. California, Arizona, Nevada), whereas green indicates increases.

Data

Drought Index Data:

We assemble a panel dataset at the state-year level to analyze alfalfa production in relation to drought and irrigation. Our primary drought metric is the Standardized Precipitation–Evapotranspiration Index (SPEI), obtained from NOAA for the period 2005–2025. SPEI is a continuous index of moisture balance (precipitation minus potential evapotranspiration) standardized over time (Vicente-Serrano et al., 2010). Positive SPEI values indicate wetter than normal conditions and negative values indicate drought; the index thus quantifies drought severity in a comparable way across regions and months. We focus on SPEI average 12 month periods to capture prolonged drought affecting a perennial forage crop - alfalfa. SPEI offers a comprehensive measure by including temperature driven evaporative demand. By using SPEI, we ensure our analysis captures both precipitation deficits and heat stress in quantifying drought. Figure 4 shows average state level SPEI, we can note that the western states are much more drought than the east (SPEI scale is indicated in the appendix table A.6).

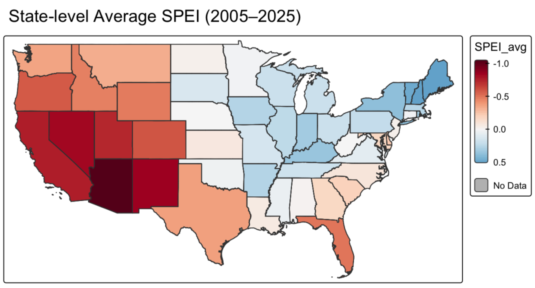

Figure 4: Average SPEI of U.S. from 2005 to 2025
Data source: NOAA Global Gridded SPI
(CMORPH Daily) — Drought.gov

Alfalfa Production:

For alfalfa production data, we draw on multiple USDA sources. State level alfalfa hay statistics (production in tons, harvested acreage in acres, and total crop value) are obtained from USDA NASS (National Agricultural Statistics Service) QuickStats. We utilize data for recent benchmark years (2013, 2018, 2023) as well as historical annual data where available. In particular, we compile a 20 years time series of state level alfalfa harvested area and production. We distinguish between irrigated and non-irrigated alfalfa where possible: the Census of Agriculture provides the percentage of hay acreage that is irrigated by county (and aggregated by state) in census years. Using these data, we classify each state by its irrigation dependence. Western states like California, Arizona, Idaho, Nevada have high irrigation shares (often well above 50%), whereas in Midwest states the share is near zero (alfalfa is rain-fed). This irrigation dependence measure is a key variable in our analysis, as it will allow us to test whether drought impacts are modulated by the presence of irrigation. We incorporate that information by including the irrigation share in regressions and by interacting drought indices with irrigation in some specifications to see if irrigation buffers the yield losses due to drought.

We also consider alfalfa's economic and trade variables. State level alfalfa export values (annual hay export revenue by state) are compiled from the USDA Global Agricultural Trade System (GATS) and recent literature (Sall et al., 2023). These data indicate how much each state's alfalfa sector earns from exports. As expected, the largest export values are observed in the Western states. Figure 4 maps the average annual export value of alfalfa hay by state, which shows that California in particular dominates, followed by other western states like Arizona and Washington. In contrast, most Midwest states have negligible export value since almost all their production is used domestically. For context on market conditions, we also track alfalfa hay prices. At the national scale, the total area planted to alfalfa has been trending modestly downward (Sall et al., 2023). The U.S. national export price of alfalfa (e.g., average CIF price per ton) exhibits year to year fluctuations due to market demand, feed alternatives, and trade dynamics (see appendix A.16-A.17). We will use price as a control variable in the models of export value, to separate the effects of drought on export through production changes from price driven revenue changes.

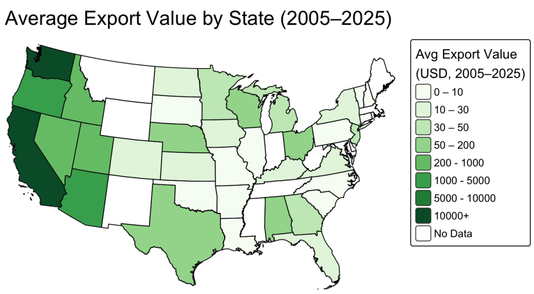

Figure 5: Alfalfa annual average export value

Notes: Average alfalfa export value by state (2005–2025, in Thousand USD). Source: USDA-NASS

Data reliability improvement:

To improve the reliability of our dataset, we implement a few data processing steps. We got the coefficient of variation (CV) for key variables (yields, production) across years or survey samples as a measure of data uncertainty. Observations with a very high CV (e.g. $> 50\%$) indicate unstable or imprecise estimates (Gbur et al., 2012). We use inverse variance weighting by $1/\text{CV}^2$, so that data points with lower uncertainty receive greater weight in the analysis. This weighted least squares (WLS) approach ensures that our results are not unduly influenced by highly noisy observations. Such an approach can reduce noise in estimates without discarding information (Gbur et al., 2012). By using these strategies, we aim to maximize the data's coverage (including smaller producing states or years with unusual conditions) while maintaining robust results. There is no change to the geographical or temporal scale of the data .

$$CV = \frac{SE}{\text{Estimate}} \times 100 \tag{1}$$

Empirical Methods

ARIMA forecasting of SPEI:

To understand the drought stress trend, we conduct Auto-Regressive Integrated Moving Average (ARIMA) and machine learning based forecasts to characterize drought trends and variability over the study period, thereby helping to disentangle drought driven changes in alfalfa production from other temporal trends. ARIMA provides a rigorous way to characterize climate variability over the period, helping isolate the effect of drought itself on yields/trade. The SPEI is treated as a climatic time series and decomposed into a long run trend component, a recurring seasonal pattern, and an irregular component capturing short run shocks. Under a multiplicative decomposition, a logarithmic transformation yields an additive representation that is amenable to statistical learning methods. The decomposed components (trend, seasonal indices, and recent residuals) are then used as predictors in a random forest model to learn nonlinear relationships between climate drivers and drought dynamics, as formalized in Equation (2).

$$SPEI = trend(t) * seasonality(t) * residual(t)$$

$$log(SPEI) = log(trend) + log(seasonality) + \epsilon_t \tag{2}$$

Figure 6 displays the SPEI trend over. The smoothed trend drifts slightly downward, consistent with a modest increase in the frequency or persistence of negative SPEI values. The grey lines indicated that individual states extreme drought or wetness events are often localized. This pattern indicates that the stochastic component of drought risk remains substantial and must be treated as an important source of production risk for forage systems. In the context of alfalfa, this helps ensure that the drought index used in regressions truly captures meaningful climate signal. The random forest help to improve the reliability of subsequent inferences about drought's impact on yield and export.

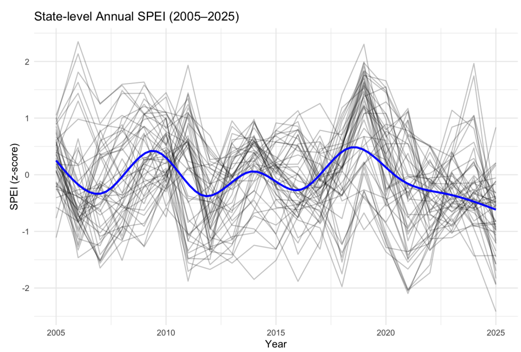

Figure 6: United State national SPEI trend Data source: NOAA

Spatial correlation in export value:

Given the geographical heterogeneity of both climate and agriculture, the study performs spatial statistical analysis to quantify how drought and alfalfa export outcomes are correlated across space. The semivariogram exhibits a clear upward trend with distance, indicating that semivariance increases as geographic separation grows (shown in and figure 7). This pattern reflects positive spatial autocorrelation: nearby states tend to experience similar moisture conditions, while differences in export value become larger at greater distances. The fitted variogram model shows a moderate nugget effect and a slow approach toward the sill, implying a large spatial range over which drought conditions are correlated (Curran, 1988). This confirms strong spatial clustering (e.g. western states versus Midwestern states) in both climate exposure and export activity.

To evaluate whether drought severity (SPEI) and alfalfa export value exhibit joint spatial structure, we computed a cross-variogram between the two variables. The cross-nugget term is slightly negative while the spatial cross-sill is small and positive, indicating that SPEI and export value do not vary together in a consistent spatial pattern. In other words, while each variable is spatially correlated on its own, their shared spatial covariance is minimal. This suggests that regional drought conditions do not align systematically with the geography of alfalfa export activity, which is likely driven more by economic and logistical factors than by climate variability. This spatial analysis ensures robust inference by highlighting that we should account for spatial clustering.

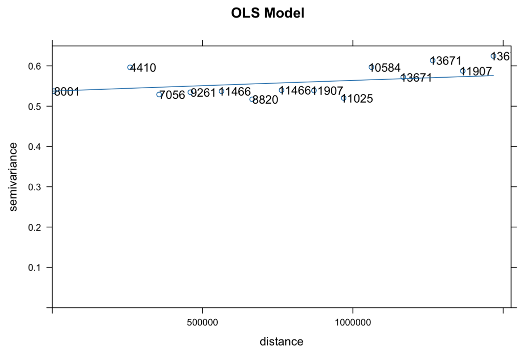

Figure 7: Spatial correlation

Table 2: Fitted Linear Model of Coregionalization (LMC) for Alfalfa Export Value

Variogram Component	**Partial Sill**	**Range(km)**
SPEI (Nugget)	0.5425	0
SPEI (Spatial)	0.0158	500
Export Value (Nugget)	3.53×10^6	0
Export Value (Spatial)	5.93×10^6	500
SPEI–Export (Nugget)	-43.51	0
SPEI–Export (Spatial)	61.60	500

The results are summarized in table 2, which lists the parameters of the fitted linear model of coregionalization (LMC) variogram components for SPEI and for alfalfa export value. The LMC indicates that both SPEI and alfalfa export value share a similar spatial correlation range of roughly 500 km (Goulard & Voltz, 1992). The fitted variograms show that alfalfa export value has a much larger spatial variance (partial sill = $5.93\times10\hat{6}$) than SPEI (partial sill = 0.0158). This indicates export outcomes are highly heterogeneous across states, whereas drought levels vary more smoothly geographically. This implies that alfalfa export value exhibit much stronger spatial heterogeneity, with a few regions persistently dominating exports, whereas SPEI varies within a relatively narrower band nationwide. These spatial correlation results confirm an important assumption for our later modeling: drought shocks are spatially correlated, so regions cannot be treated as fully independent in their climate risk.

Sum up with table 2 and figure 7, those implied that regions drought condition do not systematically coincide with those dominating alfalfa export, reinforcing the view that export patterns are driven more by economic and logistical factors than by local drought conditions.

Regression model:

To estimate the impact of drought (and irrigation) on alfalfa production and export outcomes. We employ panel regression techniques with fixed effects, drawing on best practices from agricultural economics (Hendricks & Peterson, 2012). This approach is highly appropriate for disentangling climate impacts because it controls for unobservable state-specific factors (soil, farming practices) and common yearly shocks (market or policy changes) that could otherwise confound the results (de Chaisemartin & D'Haultfœuille, 2023; Hendricks & Peterson, 2012). This is crucial in a heterogeneous setting – for example, Western states have higher baseline irrigation and export orientation, and Midwestern states have rain-fed systems Formally, our baseline model for alfalfa yield can be written as:

$$\mathrm{Y}_{st} = \beta_1 \, \mathrm{S}_{st} + \beta_2 \, \mathrm{I}_{st} + \mu_s + \lambda_t + \varepsilon_{st}, \qquad (3)$$

where Y_{st} is the alfalfa yield (tons per acre) in state s and year t, S_{st} is the drought index (with more negative values meaning drier conditions), I_{st} is the share of that state's alfalfa area that is irrigated (a measure of irrigation dependence), and μ_s and λ_t are the state and year fixed effects, respectively. The error term is ε_{st}. In this two-way fixed effects model, the coefficient β_1 captures the within state effect of a change in drought severity on yield, holding constant any state specific average yield level and any year specific shocks. By using fixed effects, we address potential omitted variable bias: any time invariant differences between. λ_t accounts for nationwide shocks like input price spikes or federal policy changes that affect all states in a given year. Our specification is in line with prior literature that uses fixed effects to study weather impacts on agriculture, ensuring that we leverage only the within unit variation (Hendricks & Peterson, 2012).

The next part of our analysis focuses on alfalfa export. We estimate models to see how drought conditions and irrigation reliance translate into economic outcomes in terms of export value. A baseline specification for export value (EV) is:

$$\mathrm{EV}_{st} = \gamma_1 \, \mathrm{S}_{st} + \gamma_2 \, \mathrm{I}_{st} + \gamma_3 P_t + \mu_s + \lambda_t + u_{st}, \qquad (4)$$

where EV_{st} is the total value of alfalfa hay exports from state s in year t (in constant dollars). This mirrors the yield model, with state and year fixed effects again accounting for unobserved heterogeneity and common shocks. Here γ_1 will tell us how drought severity in a state influences its export revenues. We hypothesize that drought (lower SPEI) will negatively impact export value by reducing production available for export (or diverting more to domestic use). The irrigation γ_2 in this context might capture whether more irrigated states maintain higher export volumes (since irrigation can buffer drought impacts and support surplus production).

We also implement fixed effects panel regressions, supplemented by generalized additive model (GAM) to quantify the relationship between drought intensity and alfalfa outcomes (yield, area, export value), while controlling for confounders and allowing for heterogeneous effects. The GAM can capture any complex nonlinear or spatial effects because it can model relationships as smooth curves rather than fixed coefficients. The spatial and cluster adjustments ensure our inference is not spuriously tight due to ignored spatial autocorrelation. Additionally, by examining both yield and acreage, our work captures the full extent of production impact (paralleling recent findings that drought induced acreage reductions contribute substantially to total crop losses (Chen et al., 2025)). In summary, the GAM adds an extra layer of confidence that the relationships are properly characterized, enhancing the study's robustness in evaluating drought effects on export across diverse geographies. The GAM specification for export value can be written as:

$$\begin{aligned} \mathrm{EV}_{st} = \theta_1 \, \mathrm{S}_{st} + \theta_2 \, \mathrm{Y}_{st} + f_1(\mathrm{Price}_{st}) \\ + f_2(\mathrm{lon}_s, \mathrm{lat}_s) + \epsilon_{st}. \end{aligned} \qquad (5)$$

where Y_{st} is yield (we include yield or production as an additional regressor to see if export value is driven more by yield changes or area), $f_1(P_t)$ is a smooth univariate function of the price (to allow a nonlinear price response curve), and $f_2(\mathrm{Lon}_s, \mathrm{Lat}_s)$ is a bivariate smooth function of the state's geographic coordinates. The term f_2 essentially acts like a spatial trend surface, meaning it flexibly accounts for broad geographic patterns in export performance (for instance, Western coastal states might consistently export more due to port access, and this advantage can be captured by a spatial smooth). By including f_2, we account for spatial heterogeneity in a non-parametric way, rather than assuming it is fully explained by our explicit variables. The GAM is fitted with a penalized spline approach, which can reveal if there are any nonlinear effects (e.g., perhaps very extreme drought has a disproportionate impact on yield beyond a linear fit, or the relationship between irrigation and export might have thresholds). The inclusion of a spatial spline in the GAM is especially useful given the earlier finding that export values have strong spatial clustering.

All our regression models are estimated with heteroskedasticity robust standard errors. Moreover, we cluster the standard errors by state (the panel unit) to allow for arbitrary autocorrelation within each state's error term across years. Clustering by state accounts for the fact that unobserved shocks could affect yields or exports over multiple years, violating the assumption of independent errors.

Results

Random forest of SPEI:

Figure 8 presents ARIMA cross-validation results evaluating forecast accuracy. The random forest model of SPEI was trained on decomposed components (trend, seasonality, residual) of the drought index to predict drought dynamics. The SPEI is decomposed into trend, seasonal, and residual components. By separating these, we can identify any long run drying trend versus regular seasonal cycles and irregular short term drought shocks. We then fit an ARIMA (Auto-Regressive Integrated Moving Average) model to the SPEI time series to model its dynamics and forecast future values.

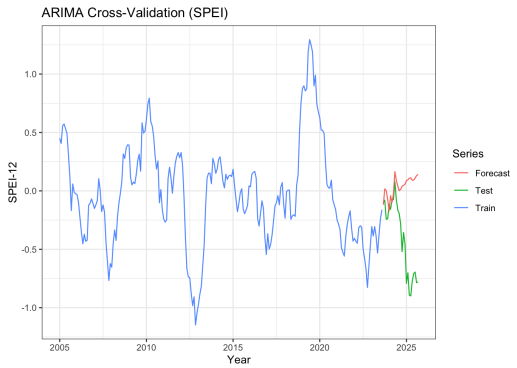

Figure 8: ARIMA Cross-Validation

Figure 8, We use cross-validation to evaluate the ARIMA model's accuracy in predicting hold out periods. In addition to ARIMA (a linear time series model), we experiment with a nonlinear machine learning approach: we train a Random Forest model on the SPEI time series that has been transformed via the decomposition. Specifically, we feed the Random Forest with features such as the current trend level, seasonal indices, and recent residuals (shocks), allowing it to capture any nonlinear interactions in how droughts develop over time (residual reported in the appendix figure A.19). This approach corresponds to equation (2) in our framework, where log(SPEI) is modeled as the sum of log-trend, log-seasonal, and random components. It indicated drought conditions have been generally worsening, and it ensures that our use of SPEI in the regressions can be justified as capturing meaningful climate variation rather than random noise.

Drought impacts on production:

Our analysis shows strong spatial heterogeneity in drought effects across the West irrigated and Midwest rain-fed regions. As shown in figure 9, Western states such as California, Washington, Idaho, and Texas cluster in the upper-right quadrant, reflecting higher drought exposure alongside relatively high yields—consistent with production systems that rely heavily on irrigation in persistently dry climates. In contrast, Midwest states such as South Dakota, Minnesota, Missouri, Nebraska, and Kansas cluster lower and more to the left, with little irrigation, moderate yields, and generally wetter conditions, reflecting predominantly rain-fed systems. Alabama lies in between, with relatively high production but only moderate irrigation. Thus, export oriented alfalfa productivity under drought is concentrated in irrigation intensive, while Midwest regions rely on rainfall and with less economic motivation (Vadas et al., 2008).

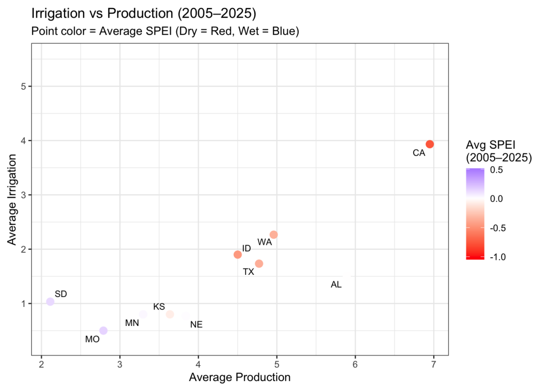

Figure 9: Scatter plot

Notes: Scatter plot showing the change in average irrigation volume (y-axis) and average alfalfa production per acre (x-axis) (HS 12) from 2005 to 2025. Point colors represent the state average SPEI (2005 - 2025), with negative values (in red) indicating drought and positive values (in blue) indicating wetness.

This spatial divergence highlights how irrigation infrastructure can mediate drought impacts, providing resilience in wet years, but creating acute vulnerability in dry years when water allocations are cut. Our findings quantitatively reinforce the narrative that water scarcity is a binding constraint on western alfalfa cultivation, with severe droughts significantly eroding the forage base in those regions. So the western irrigated states generate the bulk of export earnings, while the humid Midwest remains a domestic oriented market.

Table 3 and 4 reports the main regression estimates. The two-way fixed effects model for yield (column 1) shows that drought conditions are strongly associated with alfalfa productivity. When the model added time fixed effect, the significant level increased. In the two-way fixed-effects regressions, the coefficient on SPEI is positive and significant for yield, indicating that a one unit increase in moisture (SPEI) raises average yield by about 0.10 tons/acre ($p < 0.05$). The WLS model results indicated that CV as a weight could improve estimation accuracy even with smaller sample. This translates to a notable elasticity of yield with respect to drought severity, as evidenced by the significantly negative SPEI effect in our models. The impact on the extensive margin is similar: drought also contracts the harvested alfalfa area, suggesting that farmers respond to water stress by idling or switching fields. Indeed, our results show a significant negative elasticity of harvested acreage to drought as well. These production losses underline how profoundly water scarcity can curtail a perennial forage crop like alfalfa. These results are robust to clustering standard errors at the state-year levels.

The fixed effects specification column (1) in table 4 indicates that SPEI do not have a statistically significant effect on export value holding state and year effects constant. Columns (2) and (3) relate alfalfa export value to drought and irrigation. Column (4) reports the 2SLS results using SPEI as the instrumental variable (IV) for alfalfa yield. The SPEI shock affects export value only through its impact on yield, forming a causal chain from drought conditions to production outcomes and subsequently to trade performance. The first stage regression shows that SPEI strongly predicts yield, satisfying the relevance condition. The second stage (2SLS) results indicate that instrumented yield has a statistically significant positive effect on export value (p ¡ 0.05), implying that exogenous improvements in moisture conditions, transmitted through higher yields, translate into increased alfalfa export value.

Given export geography figure 5, it is reasonable to assume that supply side constraints resulting from the severe drought in the West would lower export volumes. Interestingly, our econometric analysis finds no significant direct link between annual drought severity and alfalfa export value once we control for fixed effects (table 4). In the two-way fixed-effects model, the SPEI coefficient is statistically insignificant, indicating that within state variation in drought does not systematically affect export earnings once time invariant state characteristics and common year shocks are controlled for. The negative SPEI effect in pooled OLS is therefore spurious, driven by spurious cross-sectional correlations (Sohil et al., 2022). The most drought prone states (low SPEI) are predominantly the high export states (California and its neighbors), so the cross-state pattern conflates climate aridity with export orientation. After removing this cross state heterogeneity with fixed effects, production losses during drought do not translate proportionally into reduced export. Irrigation is positively correlated with export orientation but becomes insignificant once fixed-effects are applied. Overall, export value appears driven primarily by market conditions rather than short run climatic fluctuations. Taken together, the evidence shows that drought shocks lower alfalfa yields in a spatially clustered way, and that these yield losses propagate along the trade pathway. When we instrument yield with SPEI, higher yields significantly raise alfalfa export value, highlighting a climate–production–export transmission channel.

Figure 10 provides a state level comparison of the change in alfalfa export value between 2017 and 2019, highlighting how tariff shock under drought conditions contributed to substantial economic losses in major producing states. The largest declines occur in Western, irrigation dependent states (such as California, Arizona, and Nevada, where multi-year drought reduced both harvested acreage and yields). In contrast, several rain-fed Midwestern states show smaller or negligible declines, consistent with their lower exposure to severe moisture deficits and export. So alfalfa production losses are spatially concentrated in arid Western systems, where water scarcity imposes stronger constraints on alfalfa.

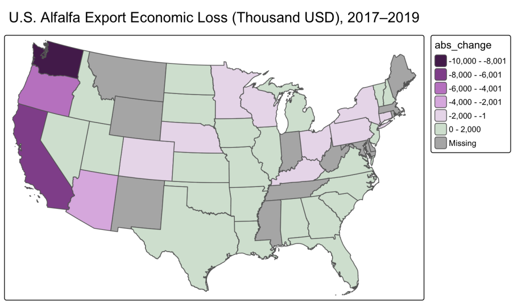

Figure 10: Alfalfa export value loss (from 2017 to 2019)

Data source: USDA - GATS

Table 3: **Table 3. Yield Models, Clustered FE and Weight Least Square**

	Cluster(state)	**Cluster(state,year)**	**Two-way FE**	**WLS**
Dependent variable	Yield/acre	Yield/acre	Yield/acre	log(production)
SPEI	0.1029 (0.0525)†	0.1029 (0.0470)*	0.1029 (0.0385)**	0.1044 (0.0594)*
Irrigation	0.0784 (0.0798)	0.0784 (0.0797)	0.0784 (0.0944)	0.2383 (0.1827)
Fixed effects	State	State + Year	State + Year	no
Observations	361	361	361	106

$^{\dagger}p < 0.10$, $^{*}p < 0.05$, $^{**}p < 0.01$. SPEI remains positive and significant across robustness checks.

Table 4: **Table 4. Comparison of Two-way FE, OLS, and GAM Models for Alfalfa Export Value**

	(1) Two-way FE	**(2) OLS**	**(3) GAM (Spatial)**	**(4) 2SLS**
Dependent variable	Export_Value	Export_Value	Export_Value	Export_Value
SPEI	−309.4 (206.8)	−1770.3*** (398.9)	−129.8 (230.3)	343.2* (145.8)
Irrigation	303.6 (528.8)	789.3 (569.2)†	253.7 (221.7)	57.15 (842.9)
Alfalfa Price (linear)	—	3.15 (6.12)	—	
Nonlinear price effect	No	No	s(Price) sig. ($p = 0.028$)	No
Spatial smooth	No	No	s(lon,lat) sig. ($p < 2 \times 10^{-16}$)	No
Fixed effects	State + Year	None	None	State + Year
Model fit	Adj. $R^2 = 0.859$	Adj. $R^2 = 0.039$	Adj. $R^2 = 0.808$ (81.5% dev.)	Adj. $R^2 = 0.780$
Observations	435	436	362	361

Notes: Standard errors in parentheses. OLS shows strong negative SPEI effect that disappears with FE. GAM reveals nonlinear price effects and strong spatial structure.

Table 5: **Table 5. GAM Smooth-Term Diagnostics**

Smooth term	**EDF**	**Ref.df**	**F**	**p-value**
s(Alf_Price_ton)	2.02	2.43	3.48	0.0277*
s(lon,lat)	8.91	8.998	101.61	$< 2 \times 10^{-16***}$

EDF = effective degrees of freedom. Spatial smooth is strongly significant, indicating strong geographical structure.

Drought impacts on alfalfa economic outcome:

To further investigate this unexpected disconnection between drought and export performance, we examined the spatial correlation between the two. The GAM results confirm the main linear findings while allowing for flexible nonlinearities. In table 4 and 5, a GAM of export value, which allows flexible nonlinear effects and spatial trends, dramatically improves explanatory power (adjusted $R^2 = 0.81$). In the GAM, we include a smooth function of latitude/longitude to capture latent spatial influences (e.g. proximity to ports or dairies) and a smooth function of alfalfa price to account for nonlinear price responses. The results show a highly significant spatial smooth term ($p < 0.01$) and a significant nonlinear price effect ($p = 0.03$). Intuitively, states located near export hubs or with established trade logistics have consistently higher export values, independent of drought status. Likewise, the relationship between price and export value is nonlinear, extreme price spikes or dips can alter export behavior in ways a linear term wouldn't capture.

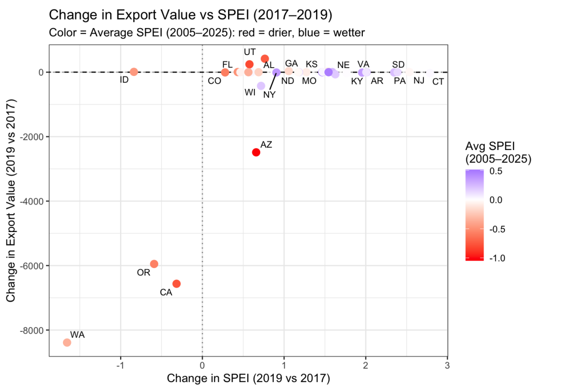

Figure 11: Scatter plot of SPEI and export value

Notes: Scatter plot showing the change in average alfalfa export value (y-axis) and SPEI changes (x-axis) from 2005 to 2025. Point colors represent the average SPEI from 2005 to 2025, with negative values (in red) indicating drought and positive values (in blue) indicating wetness.

The scatterplot in figure 11 further illustrates this disconnect: changes in SPEI between 2005 and 2025 display no clear association with changes in state-level export value, with both drought affected and wetter states exhibiting heterogeneous export responses. some highly drought affected states (red, like CA/AZ) saw only moderate export declines, and some wetter states (blue) did not translate wetness into export gains. The cross-validation results in figure 12 and figure 13 reinforce this interpretation. There is little systematic predictive alignment between changes in drought conditions and changes in export value. It indicated the geography of extreme drought does not systematically coincide with the geography of major alfalfa export production, which is instead driven more by trade and irrigation than by drought. Those visual reinforces the weak spatial coupling between climate severity and export outcomes. This pattern is consistent with the operational flexibility of export oriented western states, which may prioritize meeting export demand by reallocating hay away from domestic markets, drawing down inventories, or absorbing short run production losses.

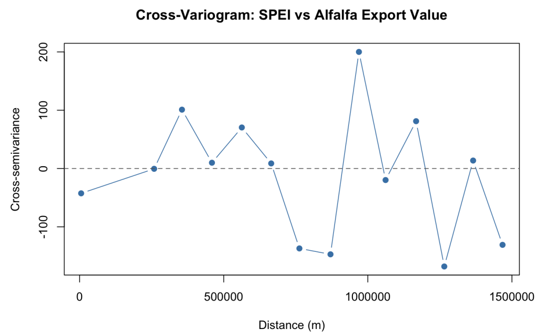

Figure 12: Cross-validation: SPEI vs Export value

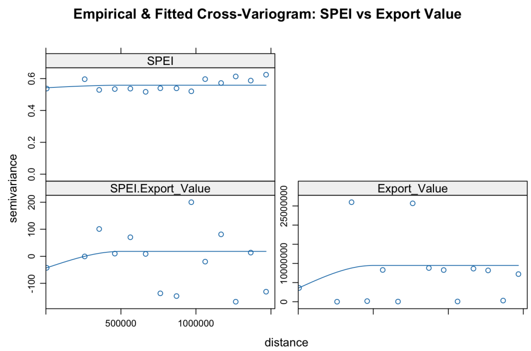

Figure 13: Fitted Cross-Validation SPEI vs export value

In summary, drought imposes a clear cost on alfalfa production, but its impact on export value is blunted by spatial and economic buffers. Alfalfa exports are concentrated in climate challenged regions, yet those same regions have infrastructure and market connectivity that help decouple export performance from year to year drought stress. Our findings suggest that improving infrastructure and trade flexibility can mitigate the economic fallout of drought. For instance, investments in water efficient irrigation and hay storage in the West could sustain production during dry spells, while enhancing transportation networks and export facilities would allow surplus from wetter regions to reach deficit areas.

In effect, market mechanisms and strategic planning can buffer the dairy and feed supply chain against localized climate shocks. Policymakers should thus view drought resilience and market access as complementary: bolstering regional resilience (through water management, crop insurance, and feed reserves) alongside maintaining open trade channels will help ensure that even as droughts increase in frequency, the economic stability of the alfalfa industry (and dependent livestock sectors) is safeguarded. The spatial and regression evidence here underscores that fostering adaptability in where and how alfalfa is produced and moved is key to weathering the challenges of a drier future.

Discussion

Our methodology combines spatial analysis of drought patterns, time series analysis of drought trends, and econometric modeling of alfalfa production. Our findings indicate that compounded drought shocks depress state level dairy revenues more than either shock alone. This highlights differential exposure and resilience across United States production systems. Quantifying drought's impact on feed supply can justify investments in climate smart adaptations. As Villoria et al. (2024) demonstrated, reducing trade frictions can alleviate food price volatility under climate shocks. In line with those insights, we recommend strategies such as enhancing hay transportation infrastructure or establishing strategic feed reserves for drought periods. We contribute a case study of how fixed-effects and spatial correlation can control for heterogeneity in interdisciplinary of economic and agronomic data. This reinforces the value of spatial economic models in agricultural research for future scholars study on similar casual effects.

Economic debates around alfalfa have been shaped primarily by agronomy and water management research, while agricultural economics evidence on the export orientation of production systems and drought exposure comparatively limited (Ottman & Putnam, n.d.). Moreover, meteorological drought is not only one determinant of alfalfa production capacity: export incentives, trade logistical advantages, and water regulations can materially mediate drought pressure by sustaining irrigation intensive production in Western states. Waring et al. (2025) found alfalfa is not just as a water intensive crop but also as a flexible one that may be a key instrument in achieving agricultural resilience against the backdrop of climate variability and recurring droughts. Our results reveal that irrigation intensive western states suffer markedly larger yield and area reductions under drought than the rain-fed Midwest. This aligns with regional farming systems: in the arid West (e.g. California, Arizona, Idaho), alfalfa relies on heavy irrigation, making it highly vulnerable to water shortages. In the Upper Midwest (e.g. Wisconsin, Minnesota), alfalfa is grown under natural rainfall and primarily for on farm use, which appears to buffer it slightly against drought impacts (albeit absolute yields are lower to begin with). The data confirm this pattern. For instance, multi-year droughts in the West have already forced reductions in irrigated alfalfa acreage. Notably, several traditionally irrigated states (such as California, Arizona, Nevada) saw sharp cutbacks in alfalfa hay area in recent years due to water scarcity and shifting crop priorities. In contrast, most Midwestern states did not appreciably reduce alfalfa plantings during the drought periods, since their production is rain-fed and largely for local feed demand and ethanol energy production (Vadas et al., 2008).

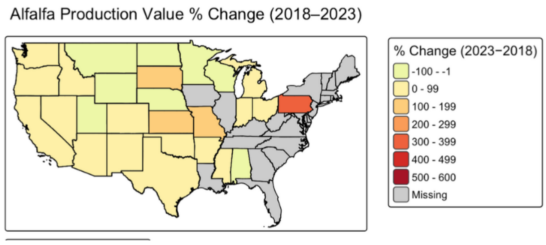

Figure 14: Alfalfa production value change
Source: USDA-NASS

Due to irrigation data availability, the estimation of did not reflect the real irrigation effects on yield. Drought not only reduce yield per acre, but also may lead farmers to alter planted area or abandon fields. In further, we can adapt Equation 4 to have the outcome as A_{st} (alfalfa area in state s, t) or the logarithm of area. We expect drought (especially severe multiyear droughts) may lead to a decline in harvested area as some farmers temporarily idle alfalfa fields or switch to other crops if irrigation water is unavailable. Indeed, in the Western states there have been instances of acreage contractions during intense drought periods. By examining these separately, we contribute to understanding whether production losses are primarily due to lower yields on the same land, or also due to fewer acres being harvested – an important distinction for policy. Advances in remote sensing, precision irrigation and decision-support tools offer opportunities to optimise water and nutrient use. Research linking physiological and molecular knowledge with digital technologies could enhance agricultural efficiency and reduce waste (Miao et al., 2025).

Conclusion

Confirming the differences between Western and Midwestern states will be important for targeted interventions. Western states may need policies focusing on water management and export market stability, since they are export oriented and irrigation dependent (e.g., water allocations, incentives for efficient irrigation, support for export logistics, as 20% of their alfalfa goes abroad). Upper Midwest states, being more livestock integrated and domestic oriented, might benefit more from feed cost assistance or crop insurance for forage, as their concern is ensuring local feed supply for dairy herds when weather reduces yields. The USDA 2023 Outlook suggested western hay prices are set by export competition [2], whereas Midwest dairy farmers rely on local hay – our research will provide evidence to support these distinctions and recommend region specific resilience measures (for example, encouraging the West dairy farms to diversify feed sourcing when alfalfa is diverted to export, or helping Midwest farmers invest in irrigation or cover crops to bolster feed in drought).

In summary, our analysis shows that drought (captured by SPEI) significantly increase alfalfa yields but have little direct impact on export values. Instead, the 2SLS results reveal a clear climate–production–export transmission pathway. When instrumented with SPEI, which indicating that exogenous improvements in moisture conditions translate into higher exports primarily through their effect on production. The GAM estimates with state level spatial smooths further document pronounced spatial heterogeneity in export outcomes across U.S. states, even after controlling for observed covariates. The SPEI and export shared minimal spatial structure, although both variables are individually spatially auto-correlated. Together, these findings underscore that climate shocks matter for production and trade, highlighting the importance of regionally targeted adaptation and production strategies in managing export risks under increasing climate variability. In the further, by accounting for land use spillovers and trade frictions as Lobell and Villoria (2023) and Villoria et al. (2024) and others have highlighted, the research that recommended adaptations (whether economic or environmental) truly enhance resilience rather than shifting problems elsewhere. The expected insights will help stakeholders balance domestic production goals with global market engagement in an era of increasing climate uncertainty.

[2] *Alfalfa Hay Outlook.* USDA, 2023

References

Ardakani, S. (2025). The Economic Impact of Drought on Alfalfa Price Formation and Irrigation Modernization Feasibility in the Western U.S. *All Graduate Theses and Dissertations, Fall 2023 to Present*. https://doi.org/https://doi.org/10.26076/3998-2534

Ben Jervey. (2014). Exporting the Colorado River to Asia, Through Hay [Section: Science]. Retrieved January 7, 2026, from https://www.nationalgeographic.com/science/article/140123-colorado-river-water-alfalfa-hay-farming-export-asia

Borton, L. R., Rotz, C. A., Black, J. R., Allen, M. S., & Lloyd, J. W. (1997). Alfalfa and Corn Silage Systems Compared on Michigan Dairy Farms. *Journal of Dairy Science*, *80*(8), 1813–1826. https://doi.org/10.3168/jds.S0022-0302(97)76116-2

Burt, J. C., Baxter, L. L., Secor, W. G., Mullenix, M. K., Stewart Jr, R. L., & Tucker, J. J. (2025). Understanding the agronomic and economic impact of contrasting harvest strategies in two alfalfa–bermudagrass mixtures in Southeastern United States. *Grassland Research*, *4*(3), 209–222. https://doi.org/10.1002/glr2.70006

Cantor, A. (2021). Hydrosocial hinterlands: An urban political ecology of Southern California's hydrosocial territory [Publisher: SAGE Publications Ltd STM]. *Environment and Planning E: Nature and Space*, *4*(2), 451–474. https://doi.org/10.1177/2514848620909384

Cantor, A., Turley, B., Ross, C. C., & Glass, M. (2022). Changes to California Alfalfa Production and Perceptions during the 2011–2017 Drought [Publisher: Routledge]. *The Professional Geographer*, *74*(4), 628–641. https://doi.org/10.1080/00330124.2022.2075409

Chen, Y., Wang, Y., Wu, C., Rosa Ferraz Jardim, A. M. D., Fang, M., Yao, L., Liu, G., Xu, Q., Chen, L., & Tang, X. (2025). Drought-induced stress on rainfed and irrigated agriculture: Insights from multi-source satellite-derived ecological indicators. *Agricultural Water Management*, *307*, 109249. https://doi.org/10.1016/j.agwat.2024.109249

Curran, P. J. (1988). The semivariogram in remote sensing: An introduction. *Remote Sensing of Environment*, *24*(3), 493–507. https://doi.org/10.1016/0034-4257(88)90021-1

de Chaisemartin, C., & D'Haultfœuille, X. (2023). Two-way fixed effects and differences-in-differences with heterogeneous treatment effects: A survey. *The Econometrics Journal*, *26*(3), C1–C30. https://doi.org/10.1093/ectj/utac017

Feuz, D. M., & Larsen, R. (2023). Factors Impacting Alfalfa Hay Prices in Seven Western States: An Explanatory Model Used for Extension Forecasting. *Western Economics Forum*. https://doi.org/10.22004/ag.econ.337176

Fleck, J. (2016). *Water is for Fighting Over: And Other Myths about Water in the West*. Island Press.

Gbur, E., Stroup, W., McCarter, K., Durham, S., Young, L., Christman, M., West, M., & Kramer, M. (2012, February). *Analysis of Generalized Linear Mixed Models in the Agricultural and Natural Resources Sciences*. 10.2134/2012.generalized-linear-mixed-models

Goulard, M., & Voltz, M. (1992). Linear coregionalization model: Tools for estimation and choice of cross-variogram matrix. *Mathematical Geology*, *24*(3), 269–286. https://doi.org/10.1007/BF00893750

Hendricks, N. P., & Peterson, J. M. (2012). Fixed effects estimation of the intensive and extensive margins of irrigation water demand [Publisher: JSTOR]. *Journal of Agricultural and Resource Economics*, 1–19. Retrieved July 2, 2025, from https://www.jstor.org/stable/23243046

Liu, Y., Wu, Q., Ge, G., Han, G., & Jia, Y. (2018). Influence of drought stress on afalfa yields and nutritional composition. *BMC Plant Biology*, *18*, 13. https://doi.org/10.1186/s12870-017-1226-9

Lobell, D. B., & Villoria, N. B. (2023). Reduced benefits of climate-smart agricultural policies from land-use spillovers [Publisher: Nature Publishing Group]. *Nature Sustainability*, *6*(8), 941–948. https://doi.org/10.1038/s41893-023-01112-w

Miao, X., Wang, G., Xu, B., Li, R., Tian, D., Ren, J., Li, Z., Fan, T., Zhang, Z., Xu, Q., Miao, X., Wang, G., Xu, B., Li, R., Tian, D., Ren, J., Li, Z., Fan, T., Zhang, Z., & Xu, Q. (2025). Study on Alfalfa Water Use Efficiency and Optimal Irrigation Strategy in Agro-Pastoral Ecotone, Northwestern China [Company: Multidisciplinary Digital Publishing Institute Distributor: Multidisciplinary Digital Publishing Institute Institution: Multidisciplinary Digital Publishing Institute Label: Multidisciplinary Digital Publishing Institute Publisher: publisher]. *Agronomy*, *15*(2). https://doi.org/10.3390/agronomy15020258

Montazar, A., Zaccaria, D., Bali, K., & Putnam, D. (2017). A Model to Assess the Economic Viability of Alfalfa Production Under Subsurface Drip Irrigation in California. *Irrigation and Drainage*, *66*(1), 90–102. https://doi.org/10.1002/ird.2091

Njuki, E. (2022). *Sources, Trends, and Drivers of U.S. Dairy Productivity and Efficiency* (ERR No. 205) (Num Pages: 52 Series: ERR-305). https://doi.org/10.22004/ag.econ.323860

Ottman, M. J., & Putnam, D. H. (n.d.). DEFICIT IRRIGATION WITH ALFALFA: WHAT ARE THE ECONOMICS?

Putnam, D., & Meccage, E. (2022). PROFITABLE ALFALFA PRODUCTION SUSTAINS THE ENVIRONMENT. *In Proceeding 2022 World Alfalfa Congress, pp.14-17.*

Rowley, C. M. (2023). *The impact of drought on U.S hay prices* [Doctoral dissertation]. Kansas State University.

Sall, I., Tronstad, R., & Chin, C. Y. (2023). Alfalfa Export and Water Use Estimates for Individual States. *Western Economics Forum*. https://doi.org/10.22004/ag.econ.337173

Sohil, F., Sohali, M. U., & Shabbir, J. (2022). An introduction to statistical learning with applications in R: By Gareth James, Daniela Witten, Trevor Hastie, and Robert Tibshirani, New York, Springer Science and Business Media, 2013, $41.98, eISBN: 978-1-4614-7137-7. *Statistical Theory and Related Fields*, *6*(1), 87–87. https://doi.org/10.1080/24754269.2021.1980261

Tucker, J. J., Mullenix, M. K., Rios, E., Basigalup, D., & Bouton, J. H. (2024). Systems management strategies for increasing alfalfa use in warm-humid regions. *Grassland Research*, *3*(2), 187–198. https://doi.org/10.1002/glr2.12080

Undersander, D. (2021). Economic Importance, Practical Limitations to Production, Management, and Breeding Targets of Alfalfa. In L.-X. Yu & C. Kole (Eds.), *The Alfalfa Genome* (pp. 1–11). Springer International Publishing. https://doi.org/10.1007/978-3-030-74466-3_1

USDA-ARS. (n.d.). Alfalfa – Breeding Insight. Retrieved January 7, 2026, from https://breedinginsight.org/alfalfa2/

Vadas, P. A., Barnett, K. H., & Undersander, D. J. (2008). Economics and Energy of Ethanol

Production from Alfalfa, Corn, and Switchgrass in the Upper Midwest, USA. *BioEnergy Research*, *1*(1), 44–55. https://doi.org/10.1007/s12155-008-9002-1

Vicente-Serrano, S. M., Beguería, S., & López-Moreno, J. I. (2010). A Multiscalar Drought Index Sensitive to Global Warming: The Standardized Precipitation Evapotranspiration Index [Section: Journal of Climate]. https://doi.org/10.1175/2009JCLI2909.1

Villoria, N. B., Arita, S., & Sydow, S. (2024). The roles of agricultural trade and trade policy in climate change adaptation and mitigation [Publisher: IOP Publishing]. *Environmental Research: Food Systems*, *1*(2), 022002. https://doi.org/10.1088/2976-601X/ad5bec

Waring, E., Dahlke, H. E., Abatzoglou, J. T., Medellín-Azuara, J., Yost, M. A., Bali, K. M., Naughton, C. C., Putnam, D. H., Sabie, R., Kishore, S., Santos, N. R., & Viers, J. H. (2025). Reimagining alfalfa as a flexible crop for water security in the Southwestern USA. *Science of The Total Environment*, *990*, 179851. https://doi.org/10.1016/j.scitotenv.2025.179851

Watch, F.
bibinitperiod W. (2025, August). Research. Retrieved January 8, 2026, from https://www.foodandwaterwatch.org/learn/research/

Worley, E., McNulty, S., Gavazzi, M., Muth, M., Southeast Regional Climate Hub (U.S.), United States. National Oceanic and Atmospheric Administration, & National Integrated Drought Information System (U.S.) (2024, October). *Drought impact reporting processes for the agriculture sector: An assessment of approaches, barriers, and opportunities in the Southeastern United States* (tech. rep.). National Oceanic and Atmospheric Administration : NIDIS : USDA Southeast Climate Hub. Research Triangle Park, North Carolina. https://doi.org/10.32747/2024.8701868.ch

A Appendix

Table A.6: Classification of drought and wetness based on SPEI values

Category	**SPEI Range**
Extremely wet	≥ 2.0
Very wet	$\geq 1.5, < 2.0$
Moderately wet	$\geq 1.0, < 1.5$
Near normal	$> -1.0, < 1.0$
Moderate drought	$> -1.5, \leq -1.0$
Severe drought	$> -2.0, \leq -1.5$
Extreme drought	≤ -2.0

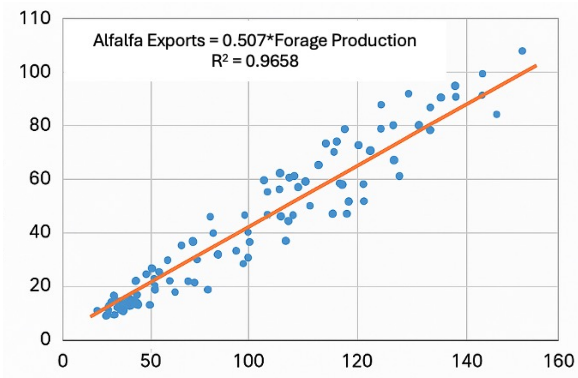

Figure A.15: United State national level alfalfa export rate
Source: (Sall et al., 2023)

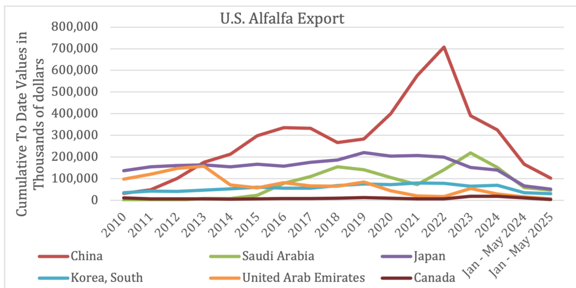

Figure A.16: Alfalfa export volume and top 6 destination
Data source: USDA-GTAS

Prices Received for Premium and Supreme Alfalfa Hay – States and 5-State Total: July 2023

State	July 2022	June 2023	July 2023
	(dollars per ton)	(dollars per ton)	(dollars per ton)
California	370.00	340.00	300.00
Idaho	320.00	290.00	280.00
Michigan	205.00	225.00	220.00
Minnesota	195.00	221.00	222.00
New York	320.00	312.00	314.00
Pennsylvania	330.00	322.00	325.00
Texas	309.00	330.00	326.00
Wisconsin	168.00	188.00	185.00
5-State Total [1] [2]	335.00	310.00	288.00

[1] 5-State total represents a weighted (hay purchases) average price for the five largest milk producing States (based on the pounds of milk produced during the previous month).
[2] For July 2022, includes California, Idaho, New York, Texas, and Wisconsin. For June 2023, includes California, Idaho, New York, Texas, and Wisconsin. For July 2023, includes California, Idaho, New York, Texas, and Wisconsin.

Figure A.17: Alfalfa domestic price
Source: USDA-NASS

Figure A.18: United State export alfalfa price

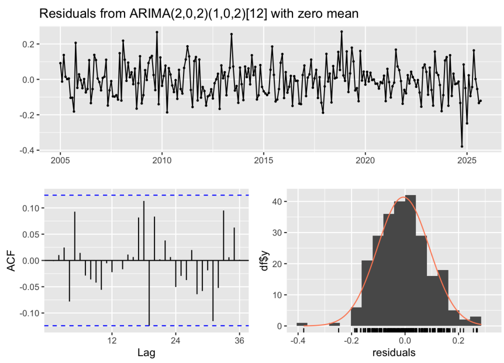

Figure A.19: Residual errors of SPEI forecast in ARIMA

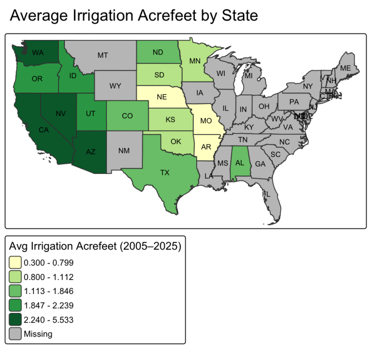

Figure A.20: Alfalfa irrigation intensive
Data source: USDA-NASS

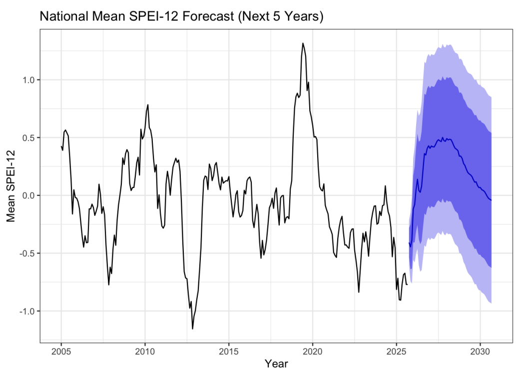

Figure A.21: Prediction of SPEI

- **SPEI calculation:** The Standardized Precipitation–Evapotranspiration Index (SPEI) extends the Standardized Precipitation Index (SPI) by incorporating the effects of evaporative demand. While SPI is based solely on precipitation anomalies, SPEI replaces precipitation with a climatic water balance variable. Formally:

$$D_t = P_t - \mathrm{PET}_t,$$

where P_t is monthly precipitation and PET_t is potential evapotranspiration. This allows SPEI to account for the impact of temperature and evaporative losses on drought intensity. The accumulated climatic water balance over a time scale k (e.g., 3, 6, or 12 months) is computed as:

$$D_t^{(k)} = \sum_{i=0}^{k-1} \left(P_{t-i} - \mathrm{PET}_{t-i} \right).$$

Following (Vicente-Serrano et al., 2010), the accumulated series $D_t^{(k)}$ is fitted to a three-parameter log-logistic distribution:

$$F(D) = \left[1 + \left(\frac{\alpha}{D - \gamma} \right)^{\beta} \right]^{-1},$$

where α, β, and γ represent the scale, shape, and location parameters. The cumulative probability $F(D)$ is then transformed into a standard normal deviate:

$$\mathrm{SPEI} = \Phi^{-1}\big(F(D)\big),$$

where Φ^{-1} is the inverse of the standard normal distribution. This procedure mirrors the normalization step of SPI but applied to moisture deficit rather than precipitation alone, allowing SPEI to capture both precipitation shortages and heat-driven evaporative stress.

Data and coding open access

R coding share: https://github.com/liyoumin/Geospatial-AgEcon/tree/main/project