# Impact of Drought on U.S. Alfalfa Production and Export

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## Abstract

Drought threatens the stability of the U.S. 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 integrate geospatial diagnostics with panel econometric models. We find that drought significantly reduces yields, with irrigated Western states experiencing the largest contractions, reflecting structural dependence on irrigation water resources. Spatial diagnostics show near-zero cross-covariance between SPEI and export value, but both variables show significant spatial autocorrelation independently. The fixed-effects estimates eliminate the spurious negative relationship observed in pooled regressions. Our findings underscore the need for region-specific adaptation strategies for irrigation water efficient 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) estimate drought impacted area of different agricultural commodity, roughly one-third of alfalfa acreage was in areas affected by drought in 2025 in the United States, underscoring this crop's exposure to water stress.

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 |
| Hog Inventory | 33 |

Climate extremes like the multi-year Western drought have curtailed alfalfa hay output, 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 Western states is exported) (Sall et al., 2023). And alfalfa is export-oriented, water-dependent systems in western states (Borton et al., 1997). 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. Absent mitigation measures, the environmental impact of northern U.S. dairy production is expected to increase by 2050, and feed production is maintained as increased forage yields compensate for reduced corn grain yields (Putnam & Meccage, 2022; Veltman et al., 2021). Lobell and Villoria (2023) and Tucker et al. (2024). demonstrate that ostensibly climate-smart practices can have unintended global spillovers: a 5% productivity drop (e.g. from cover cropping) can erase 70–80% of the net climate benefit once land-use changes are accounted for. This finding warns that domestic agricultural adaptations can shift production (and emissions) abroad, highlighting the impor-

[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.

tance 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. These studies suggest that trade frictions and climate shocks are deeply connected to economic outcomes in agriculture.

Figure 1 shows average acres alfalfa of each states over past 20 yearss. Alfalfa acreage peaked in the early 2000s and has declined in many areas, partly reflecting water limitations and competition from other crops. In Western states, alfalfa is heavy irrigation demands and export-oriented production. Given those context, our study is motivated to quantify how drought conditions affect U.S. alfalfa production and whether these effects exhibit spatial patterns. We also seek to integrate the climate and trade dimensions noted by prior research. For example, reducing crop productivity through stress or conservation measures can have spillovers – a 5% on-farm yield drop can erode 70–80% of the net climate benefit of a practice once global land-use change is considered (Lobell & Villoria, 2023). Likewise, trade policy can buffer or exacerbate climate shocks: eliminating trade frictions has been shown to dampen price spikes during climate extremes by facilitating imports (Villoria et al., 2024). In sum, the background evidence suggests that alfalfa's vulnerability to drought is a nationally important issue that spans biophysical and economic domains. The following methodology outlines how we investigate this, combining spatial drought analysis and econometric modeling to untangle the effects of drought on alfalfa yields, acreage, and export value.

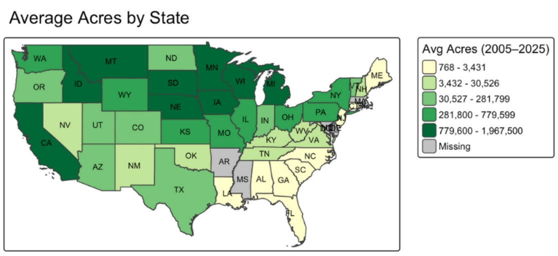


Figure 1: Alfalfa average annual acreage
Source: USDA-NASS

# Background

Alfalfa is the third most valuable field crop nationally (about 23 million acres harvested, worth $8.7 billion annually) and is paradoxically both drought-tolerant biologically and water-intensive agronomically. 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. Prolonged rainfall shortages thus pose a significant threat: multi-year droughts in the western U.S. have already curtailed alfalfa hay output, with ripple effects on dairy feed supply. Western states such as California and Arizona are especially vulnerable because they rely on irrigation and also export a significant share of their alfalfa production.

In figure 2 and appendix figure A.15 indicate alfalfa export rate (the percentage of production that is exported), about 50% of export forge is alfalfa in U.S. and more than 20% alfalfa hay production is shipped overseas (Sall et al., 2023), creating an export-oriented, water-dependent production system in that region (Borton et al., 1997). 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 Southwest. 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). 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). Together, these papers reposition alfalfa as a flexible crop within basin-scale water management. Extension and industry guidance detail management/irrigation practices to stabilize yields and quality in arid regions (Hanson et al., 2008). USDA-ERS documents strong TFP growth in large-herd Western/Southwestern states and slower gains in smaller herds/organic, mapping the structural shift toward scale and regional concentration (Njuki, 2022). It is not clear that how irrigation and drought impact on alfalfa production. 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.

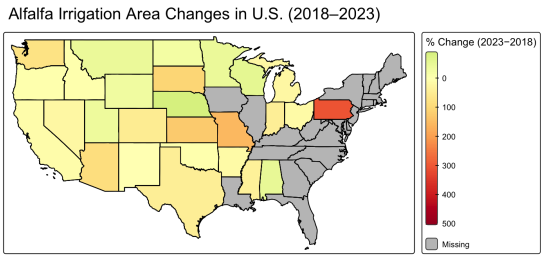


Figure 3: Alfalfa irrigation area changes

*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. Gray indicates minimal change or missing data. Western irrigated regions show the largest contractions in alfalfa area during recent drought years.

# 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 accumulated 12 month periods to capture prolonged drought affecting a perennial forge crop - alfalfa. SPEI offers a comprehensive measure by including temperature-driven evaporative demand. By using SPEI (and cross-checking with USDM), 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 states in west of rocky mountain are much more drought than the east (SPEI scale is indicated in the appendix table A.6).

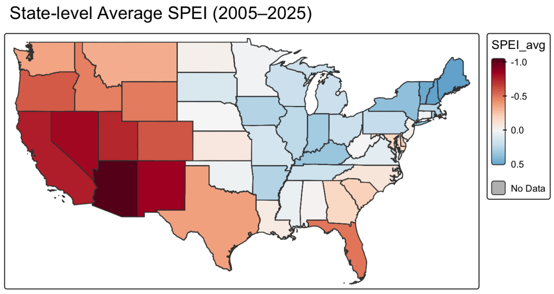


Figure 4: Average SPEI of U.S. from 2005 to 2025
Data source: NOAA

## 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-year 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 Midwestern 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 (reflecting its large production and export rate), followed by other western states like Arizona and Washington. In contrast, most Midwestern states have negligible export value since almost all their production is used domestically. For context on market conditions, we also track alfalfa hay prices. 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 shows the state-level alfalfa export value, it is immediately clear that western states dominate export activity. California, Arizona, Washington state, and other arid Western states ship out a high share of their hay (often over 20%), whereas Midwestern producers export virtually lower, consuming their alfalfa on local dairy farms. This again underlines the West's dual dependence on steady water supplies and export markets. At the national scale, the total area planted to alfalfa has been trending modestly downward (Sall et al., 2023).

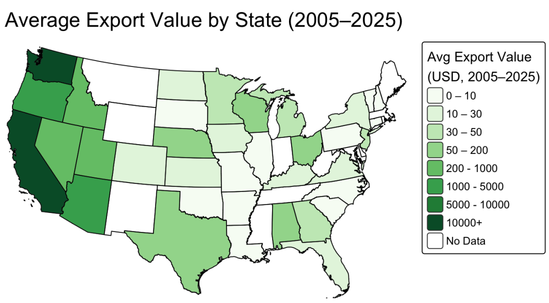


Figure 5: Alfalfa annual average export value

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

## Data reliability improvement:

We matched state-level alfalfa production and irrigation data with U.S. map polygons. 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 $1/\mathrm{CV}^2$, 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.

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

# Empirical Methods

## ARIMA forecasting of SPEI:

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. 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. It emphasized that drought risk is characterized by both strong interannual variability and substantial cross-state dispersion rather than a simple monotonic trend.

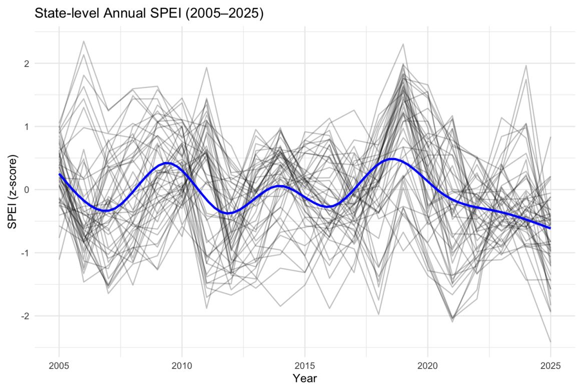


Figure 6: United State national SPEI trend
Data source: NOAA

## Spatial correlation in export value:

To assess the spatial structure of export and drought across states, we computed an empirical semivariogram of the export value. 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 (using standard OLS estimation) 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 behavior is consistent with the physical nature of climatic processes, which evolve smoothly over space rather than shifting abruptly at administrative boundaries.

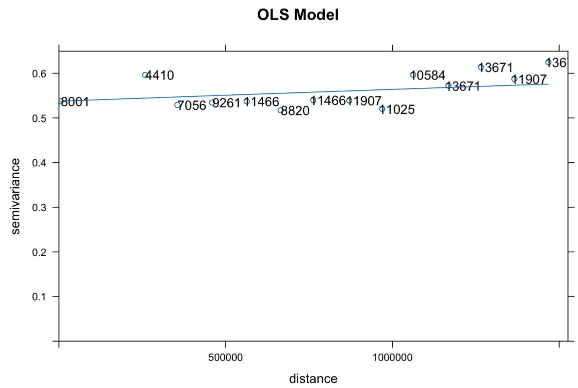


Figure 7: Spatial correlation

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.

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) | $3.53 \times 10^6$ | 0 |
| Export Value (Spatial) | $5.93 \times 10^6$ | 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 = $5.93\times 10\hat{6}$) 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:

We implement fixed-effects panel regressions, supplemented by instrumental variables and 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. This multi-pronged strategy strengthens our analysis by cross-validating findings in multiple ways. The fixed-effects approach provides an estimate of drought's impact that controls for unobservable differences and common shocks, which is crucial for credibility (de Chaisemartin & D'Haultfœuille, 2023; Hendricks & Peterson, 2012). The spatial and cluster adjustments ensure our inference is not spuriously tight due to ignored spatial autocorrelation. Some studies suggest irrigated crops can experience smaller yield losses under drought compared to rainfed crops (Chen et al., 2025; Worley et al., 2024), so we test that by interacting SPEI with irrigation contexts. 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)).

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). The use of a panel (state-by-year in our case) allows us to difference out unobserved factors that are constant within each state (such as soil quality, long-run climate, or farming practices) and common shocks across years (such as nationwide price trends or policy changes). This is implemented by including state fixed effects and year fixed effects in the regression. 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 $\mu_s$ and $\lambda_t$ are the state and year fixed effects, respectively. The error term is $\varepsilon_{st}$. In this two-way fixed effects model, the coefficient $\beta_1$ 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. $\lambda_t$ 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 $\gamma_1$ 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 $\gamma_2$ in this context might capture whether more irrigated states maintain higher export volumes (since irrigation can buffer drought impacts and support surplus production).

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.

We also incorporate a GAM to allow more flexible relationships and capture any spatial nonlinearity directly. 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, capturing any broad spatial gradients in export value (for example, West Coast states might on average have higher export values even after accounting for other factors, due to port access). 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.

# 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.

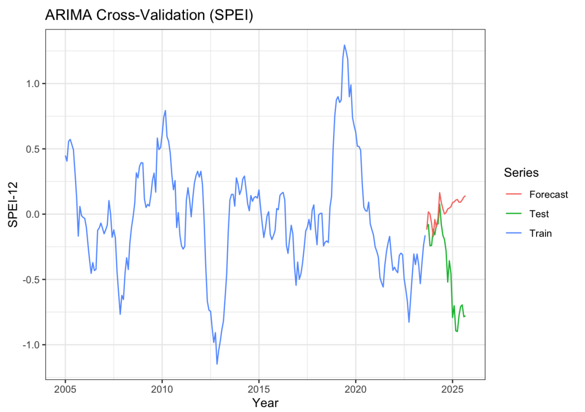


Figure 8: ARIMA Cross-Validation

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 western irrigated and Midwestern rain-fed regions. As figure 9 shown, western states like California, Washington, Idaho, and Texas appear to the upper right and are more drought, indicating that they combine high yields and heavy irrigation under chronically drier climates. In contrast, Midwestern 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. So high alfalfa productivity under drought is sustained mainly in irrigation-intensive western systems, while wetter regions rely on rainfall with lower irrigation inputs.

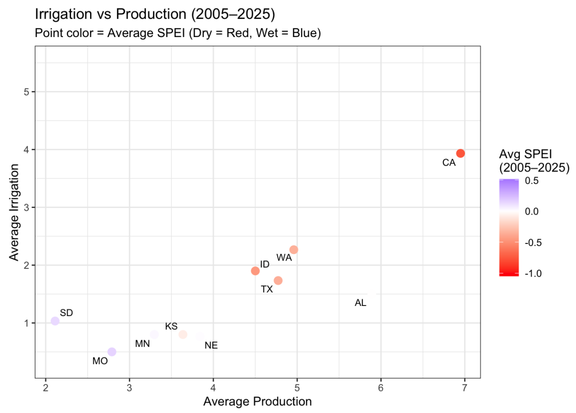


Figure 9: Scatter plot

*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, one might expect that severe drought in the West would translate into lower export volumes (through reduced supply). Interestingly, our econometric analysis finds no significant direct link between annual drought severity and alfalfa export value once we control for fixed effects (indicated in 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 large negative SPEI effect in pooled OLS is therefore spurious, driven by spurious cross-sectional correlations. 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. This likely reflects the ability of export-oriented states to buffer logistic cost, or prioritization of contract fulfillment. Irrigation is positively correlated with export orientation but becomes insignificant once fixed effects are applied. Overall, export value appear 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.

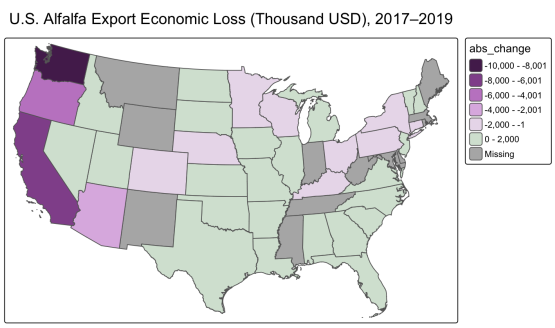


Figure 10: Alfalfa export value loss (from 2017 to 2019

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)$^{\dagger}$ | 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)$^{\dagger}$ | 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.

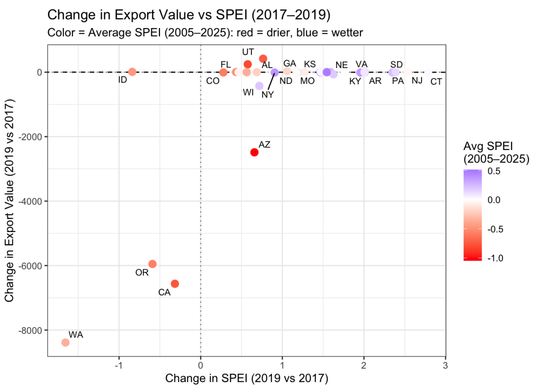


Figure 11: Scatter plot of SPEI and export value

*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, suggesting that climate-related production shocks do not translate proportionally into export fluctuations. 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.

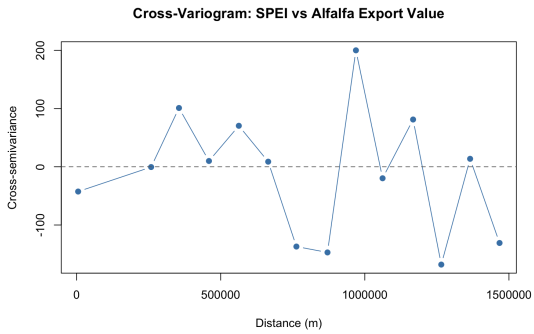


Figure 12: Cross-validation: SPEI vs Export value

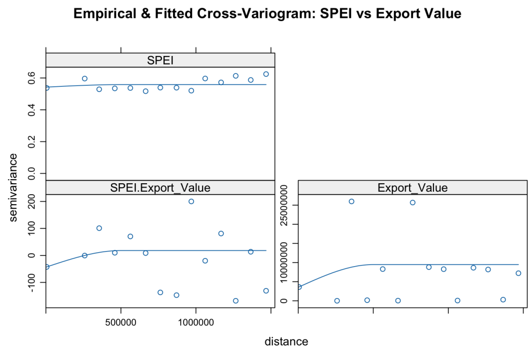


Figure 13: Fitted Cross-Validation SPEI vs export value

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 U.S. 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. By citing (Hendricks & Peterson, 2012) and adopting their econometric approach, 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.

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 same drought periods, since their production is rain-fed and largely for local feed demand.

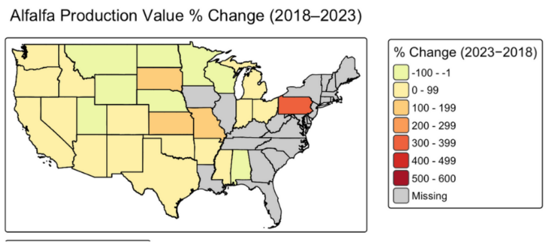


Figure 14: Alfalfa production value change
Source: USDA-NASS

Due to irrigation data avaliability, 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.

## 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 Midwestern 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 Midwestern dairy farmers rely on local hay – our research will provide evidence to support these distinctions and recommend region-specific resilience measures (for example, encouraging Western dairy farms to diversify feed

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

sourcing when alfalfa is diverted to export, or helping Midwestern 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.

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# A Appendix

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

| **Category** | **SPEI Range** |
|---|---|
| Extremely wet | $\geq 2.0$ |
| 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 | $\leq -2.0$ |

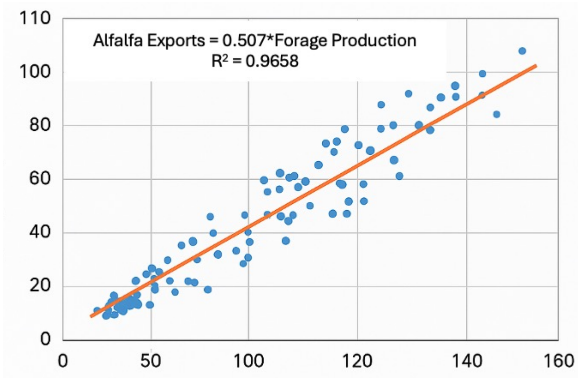



Figure A.15: United State national level alfalfa export rate

Source: (Sall et al., 2023)

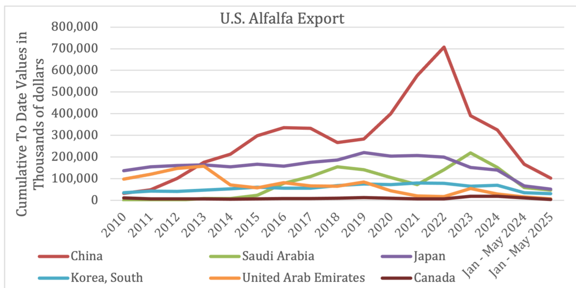
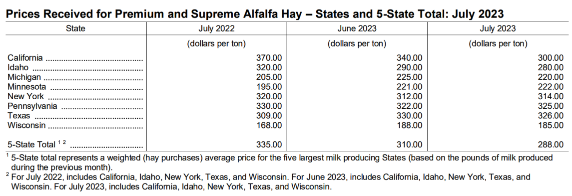



Figure A.16: Alfalfa export volume and top 6 destination

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

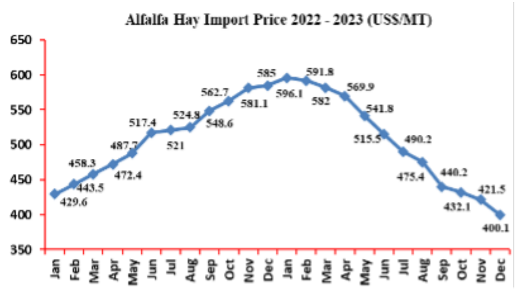



Figure A.18: United State export alfalfa price

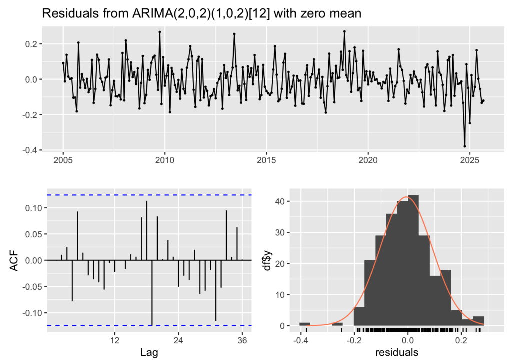



Figure A.19: Residual errors of SPEI forecast in ARIMA

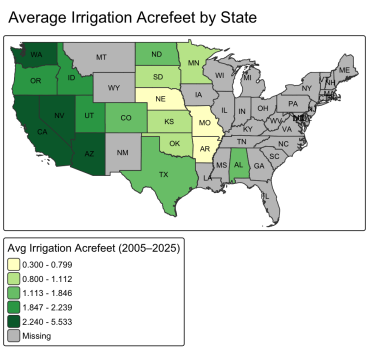



Figure A.20: Alfalfa irrigation intensive
Data source: USDA-NASS

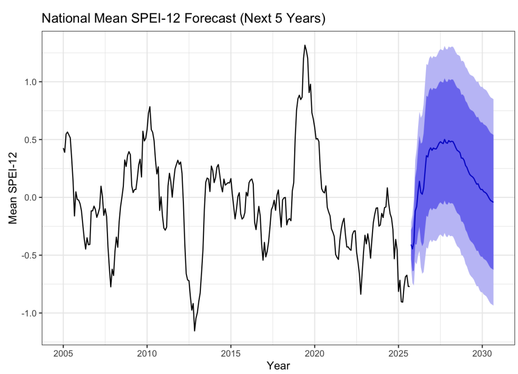



Figure A.21: Prediction of SPEI

- **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 $\mathrm{PET}_t$ 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:

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

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 $\alpha$, $\beta$, and $\gamma$ 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 $\Phi^{-1}$ 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