Changing weather distributions and US agricultural land use

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Abstract

We develop novel distributional weather measures to examine U.S. agricultural land use adaptation to climate shifts. Using location-specific z-scores and Wasserstein distance to quantify distributional changes between baseline and recent climate normals, we analyze cropland transitions from 2008 to 2024. Results show mean temperature shift captures the primary climate signal nationally, but significant regional heterogeneity exists. These findings suggest conventional analyses relying on mean-based measures may overlook important climate dimensions, particularly where changes in variability or extreme event frequency diverge from central tendency trends.

Keywords: Weather distributions, Wasserstein distance, land-use

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1 Introduction

Shifting weather distributions pose a fundamental challenge for agricultural systems worldwide. While a substantial literature documents temperature and precipitation impacts on crop yields, the behavioral dimension of adaptation—how farmers adjust what they produce and where—has received far less attention. Land use transitions represent a primary margin of long-term adaptation: producers facing persistent changes may reallocate land to better-suited uses rather than accept lower yields on existing crops. Understanding whether this adaptation is occurring is essential for increasing profitability, improving risk management, and ensuring long-term land productivity.

Two features of the existing literature limit our understanding of climate-driven land use change. First, research focuses almost exclusively on yield outcomes rather than land use decisions—the very margin where long-run adaptation may be most pronounced. Second, while some land use studies incorporate variability or extreme event indicators, none characterize the full distribution of weather outcomes or track how these distributions evolve over time. Climate change alters not just average conditions but variance, skewness, and tail behavior simultaneously—dimensions that piecemeal measures of variability or threshold exceedances cannot fully capture.

This study addresses these gaps through two methodological innovations. First, we transform daily temperature data into z-scores using location-specific 30-year normal distributions, capturing whether conditions are abnormal relative to local expectations rather than imposing uniform absolute thresholds. Second, we employ the Wasserstein distance, a metric from optimal transport theory, to quantify comprehensive distributional shifts between baseline and recent climate normals. Unlike mean-based measures, Wasserstein distance captures changes in variance, skewness, and tail behavior simultaneously.

We apply these measures to analyze cropland transitions across the contiguous United States from 2008 to 2024, combining USDA Cropland Data Layer land use data with NASA Daymet daily weather data. Our panel of over 100 million pixel-year observations enables identification of weather-related effects while controlling for time-invariant location characteristics and regional economic shocks through high-dimensional fixed effects.

Our results reveal that cumulative distributional shift, measured by Wasserstein distance, is associated with reduced cropland share nationally (1.4–1.8 percentage points per 1°C increase). A two-stage decomposition isolating higher-order distributional changes shows that mean temperature shift captures much of the climate signal at the national level. However, this aggregate finding masks substantial regional heterogeneity. In the Heartland, warming means are associated with cropland expansion, but changes in temperature variability exert a countervailing negative effect. In the Southern Seaboard, Fruitful Rim, and Basin and Range, mean shift shows no significant relationship with cropland, yet the Wasserstein residual is highly significant. These patterns suggest that the value of distributional climate measures depends critically on regional production systems and the specific nature of local weather changes.

2 Previous Literature

Economic research on weather and climate impacts on agriculture has expanded substantially, though most work focuses on crop yield responses rather than land use decisions[1;2;3]. Studies have demonstrated that U.S. corn and soybean yields exhibit strong nonlinear responses to temperature, increasing up to crop-specific thresholds before declining sharply[4]. This bin-based methodology has been extended to wheat[5], sorghum[6], and crops in other regions[7]. For livestock, the temperature-humidity index has documented heat stress effects on dairy cattle productivity and mortality[8;9].

A separate literature distinguishes short-run weather impacts from long-run climate adaptation. Researchers comparing immediate yield responses with cross-sectional climate differences found limited evidence of adaptation in U.S. corn production[10]. This work was formalized by demonstrating that agricultural systems are jointly biological and managerial: producers calibrate management to local climate expectations, creating a "climate penalty" when weather deviates from these expectations[11]. Recent global estimates suggest adaptation offsets some but not all climate damages, with notable variation across crops and regions[12].

Research directly examining land use adaptation remains sparse[13;14]. For the U.S., studies using fractional multinomial logit frameworks have examined land shares in the Pacific Northwest[15] and nationally at 10 km resolution[16], finding nonlinear responses to degree-days, precipitation, and drought indicators. Both document thresholds beyond which cropland shares decline and pasture expands, with precipitation and temperature variability reducing cropland shares. European studies find similar climate sensitivity in France[17] and Nordic countries[14], where growing degree days increase cereal shares while higher precipitation favors grassland. At the global scale, research tracking crop migration found that maize, wheat, and rice distributions shifted toward cooler regions as mean temperatures rose, while soybeans expanded into warmer zones coinciding with breeding improvements[13].

Across studies, land use responses are sensitive to weather distributions, highlighting the importance of modeling extremes when evaluating adaptation. However, two limitations persist. First, while some studies examine mean conditions and deviations, none characterize the full distributions of weather variables or their evolution over time, even though changes across distributional moments may directly affect producer decisions. Second, the literature has focused on yield outcomes rather than land use transitions, the primary margin of long-term adaptation. Farmers facing persistent changes may respond not by accepting lower yields but by reallocating land to better-suited uses. Understanding this adaptation requires examining land use directly.

3 Methods

We develop two new weather measures to assess the impact on land use transitions. The first captures annual weather deviations or abnormalities and the second captures distributional change. Both use the distribution of weather patterns from 1980 to 2009 to form the baseline 30-year normal distribution. A description of these measures is available in the appendix.

3.1 Regression methodology

We apply these weather and climate measures to analyze cropland expansion and contraction in the US using a panel fixed-effects regression (equation 9). This regression includes z-score and SPI weather shocks during the planting season as well as measures of distributional change using the Wasserstein temperature and precipitation measures. We include pixel-level and year fixed-effects to account for geographic heterogeneity and temporal heterogeneity. We also include region (or state) by year fixed-effects to account for changes in the relative profitability of crops versus other uses within a given year. Our outcome variable is the share of land in the 1km pixel that is identified as cropland in that year.

$$LandUseShare_{it} = \sum_{m=1}^{4} \alpha_m \cdot \text{ZscoreBin}_{it}^{m} + \sum_{m=1}^{4} \beta_m + \Gamma \cdot W_{it} \cdot \text{SPI}_{it}^{m} + \tau_r + \omega_t + \gamma_{rt} + \alpha_i + \varepsilon_{it} \quad (1)$$

To assess whether the Wasserstein distance captures relevant information beyond simple mean temperature shifts, we implement a two-stage decomposition approach. This methodology addresses the inherent correlation between Wasserstein distance and mean shift—since distributions that shift in mean will mechanically exhibit positive Wasserstein distance—while isolating the contribution of higher-order distributional changes (variance, skewness, and tail behavior). In the first stage, we regress Wasserstein distance on mean temperature shift, absorbing pixel and year fixed effects:

$$W_{it} = \alpha + \beta \cdot \Delta\bar{T}_{it} + u_{it} \quad (2)$$

where W_{it} is the Wasserstein distance for pixel i in year t, $\Delta\bar{T}_{it}$ is the corresponding mean temperature shift, and u_{it} is the residual capturing distributional changes beyond the mean. The R^2 from this regression indicates what share of Wasserstein variation is attributable to mean shift alone, with $(1 - R^2)$ representing the contribution of variance, skewness, and tail changes. In the second stage, we regress cropland share on both the mean shift and the first-stage residual:

$$Y_{it} = \gamma_1 \cdot \Delta\bar{T}_{it} + \gamma_2 \cdot \hat{u}_{it} + \mathbf{X}'_{it}\boldsymbol{\delta} + \mu_i + \tau_t + \epsilon_{it} \quad (3)$$

where $\hat{u}_{it}$ is the estimated residual from the first stage and $\mathbf{X}_{it}$ includes additional controls. By construction, $\hat{u}_{it}$ is orthogonal to the mean shift, eliminating concerns about multicollinearity. A significant coefficient γ_2 indicates that distributional changes beyond the mean—such as increased temperature variability or more frequent extremes—independently affect land use decisions, validating the use of Wasserstein distance over simpler mean-based climate metrics.

4 Data

The Cropland Data Layer (CDL), created by the National Agricultural Statics Service (NASS), provides data about land use by type at a resolution of 30m from 2008 to 2024. This data is compiled from satellite images throughout the growing season. The documentation notes that while these images exist throughout the growing season, the data is more closely aligned with planted acres than harvested acres. The weather data comes from NASA's Daymet database. This database has daily information on temperature and precipitation at a resolution of 1 km for North America beginning in 1980. The CDL data and the weather data are at two different levels of aggregation. In order to marry the two datasets, we aggregated the CDL data to the 1 km resolution to match the weather data. In doing so, we calculated the share of each 1 km pixel that contained cropland. We also make use of ERS's resource regions (see appendix). These are geographic areas that were designed to reflect geographic agricultural specialization.

5 Results

5.1 Summary statistics

From 2008 to 2024, the amount of land devoted to crops expanded in some areas while contracting in other areas of the US. The cropland share of each 1km pixel are presented in figure 1 for 2008 (panel A) and 2024 (panel B) while panel C presents the change in cropland shares between these two years. Declines in cropland share were most pronounced in the Southern and Eastern United States, with the Eastern Uplands, Southern Seaboard, and Northern Crescent showing significantly larger decreases than the Heartland, Northern Great Plains, Basin and Range, and Fruitful Rim.

[Figure 1 about here.]

We summarize the remaining variables in the appendix.

5.2 Regression results

Table 1 presents estimates of weather and climate effects on cropland share across three fixed effects specifications. The dependent variable is the percentage of land in crops at the 1km grid cell level. All specifications include pixel and year fixed effects, with progressively richer controls: Column (1) includes only pixel and year fixed effects, Column (2) adds ERS region-by-year interactions, and Column (3) adds state-by-year interactions. The results are robust across specifications: extreme temperature days during the planting season are associated with modest increases in cropland share (approximately 0.06–0.09 percentage points per additional day), while cumulative climate shift, measured by the lagged Wasserstein temperature distance, has a consistently negative and statistically significant effect (approximately 1.4–1.8 percentage points per unit increase). Precipitation climate shift shows no significant effect, and wetter planting season conditions (higher SPI) are associated with reduced cropland.

[Table 1 about here.]

Regional estimates reveal substantial heterogeneity in these relationships (see appendix). The Wasserstein temperature measure shows negative associations with cropland share in the Northern Crescent, Prairie Gateway, Eastern Uplands, Fruitful Rim, and Basin and Range, consistent with heat-related stress or reduced moisture retention. In sharp contrast, the Heartland was the only region to exhibit a positive and statistically significant relationship between Wasserstein temperature and cropland expansion. Weather shocks also vary regionally: hot days during planting show positive associations with cropland in several regions, while wetter-than-normal planting conditions (higher SPI) reduce cropland share in nearly every region.

To assess whether the Wasserstein measure contributes information beyond mean shifts, we implement the two-stage decomposition outlined in equations 2 and 3. The full-sample results in Table 2 suggest that the Wasserstein measure does not provide statistically significant information beyond mean temperature shift at the national level.

[Table 2 about here.]

However, regional decomposition reveals that Wasserstein contributes additional information in specific production systems (see appendix). In the Heartland, mean shift is associated with increased cropland share while the Wasserstein residual shows a countervailing negative effect, suggesting that changes in temperature variability dampen the positive effects of warming means. In the Northern Crescent, Prairie Gateway, and Eastern Uplands, the Wasserstein residual contributes no additional information beyond mean shift. Most notably, in the Southern Seaboard, Fruitful Rim, and Basin and Range, mean shift shows no significant relationship with cropland, yet the Wasserstein residual is statistically significant—indicating that cropland changes in these regions respond to distributional shifts beyond changing means.

6 Discussion

The aggregate results from the two-stage decomposition suggest that, for the United States as a whole, mean temperature shift captures much of the climate signal relevant to agricultural land use decisions. The Wasserstein residual, representing changes in variance, skewness, and tail behavior beyond the mean, does not achieve statistical significance in the pooled sample. This finding provides some reassurance that the extensive literature relying on mean-based climate measures may not be systematically missing critical information about climate impacts on agriculture. For researchers and policymakers seeking parsimonious models of climate-agriculture relationships, these results suggest that mean shift remains a reasonable first-order approximation of climate change effects on land use.

However, this aggregate finding masks substantial regional heterogeneity that carries important implications for understanding climate adaptation. The first-stage R^2 varies dramatically across ERS resource regions, ranging from 0.14 in the Northern Great Plains to 0.97 in the Basin and Range. This variation indicates that the relationship between mean shift and overall distributional change is not uniform: in some regions, knowing the mean shift tells you nearly everything about how the distribution has changed, while in others, it captures less than one-fifth of the distributional shift. The Northern Great Plains, Heartland, and Northern Crescent, regions central to U.S. crop production, all exhibit first-stage R^2 values below 0.65, suggesting that distributional changes beyond the mean may be particularly relevant in these agriculturally important areas.

The regional two-stage results reveal three distinct patterns in how agricultural land use responds to climate shifts. First, in the Heartland, the mean shift coefficient is positive while the Wasserstein residual is significantly negative, indicating countervailing effects: warming mean temperatures appear to favor cropland expansion, but accompanying changes in temperature variability or extremes dampen this effect. Second, in the Southern Seaboard, Fruitful Rim, and Basin and Range, mean shift shows no significant relationship with cropland, yet the Wasserstein residual is highly significant. This pattern suggests that in these regions, it is not the shift in average conditions but rather changes in the distribution's shape, perhaps increased variability or altered extreme event frequency, that drives land use adjustments. Third, in regions like the Northern Crescent, Prairie Gateway, and Eastern Uplands, the residual contributes no additional explanatory power, suggesting that mean-based measures adequately capture the relevant climate signal for these production systems.

These findings point toward a nuanced conclusion regarding the value of distributional climate measures. While simpler mean-based approaches may suffice for broad national assessments or for regions where mean and distributional shifts are highly correlated, the Wasserstein distance and similar measures offer meaningful additional information in specific contexts. Regions experiencing decoupled changes in means and higher moments, or where production systems are particularly sensitive to variability and extremes, may require distributional measures to fully characterize climate impacts. Future research might fruitfully investigate why certain regions exhibit sensitivity to distributional changes while others do not, potentially linking these patterns to crop portfolios, irrigation infrastructure, or the baseline climate variability to which local agricultural systems are already adapted.

7 Conclusion

This study introduces the Wasserstein distance as a comprehensive measure of climate distributional change and examines its relationship with agricultural land use across the contiguous United States. Our results demonstrate that while mean temperature shift captures the primary climate signal at the national level, significant regional heterogeneity exists in how agricultural systems respond to distributional changes. In several key agricultural regions (including the Heartland, Southern Seaboard, Fruitful Rim, and Basin and Range) changes in the temperature distribution beyond the mean significantly influence cropland allocation. These findings suggest that conventional climate-agriculture yield analyses relying solely on mean-based measures may overlook important dimensions of weather shifts in specific regional contexts, particularly where shifts in variability or extreme event frequency diverge from trends in central tendency.

A natural extension of this work involves further decomposing the Wasserstein residual to identify which specific distributional features drive the observed land use responses. In regions where the residual is statistically significant, future research should examine whether changes in variance, skewness, or kurtosis, or particular combinations thereof, are responsible for the detected effects. Such decomposition would clarify whether farmers are responding primarily to increased temperature variability, more frequent extreme heat or cold events, or other higher-order changes in growing conditions. This investigation would not only deepen our theoretical understanding of climate adaptation mechanisms but also provide actionable guidance for agricultural policy and climate risk assessment, enabling more targeted interventions in regions where specific distributional changes pose the greatest challenges to agricultural production.

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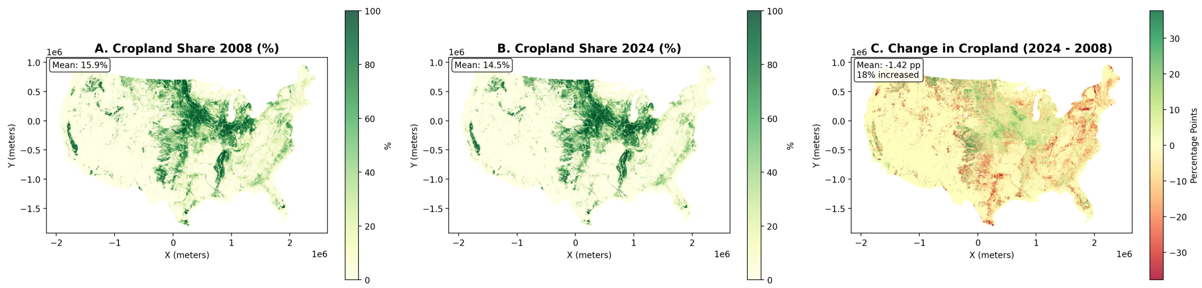

Figure 1: Change in cropland share (2008 to 2024) using USDA, NASS CDL data

Table 1: Effect of Weather Extremes and Climate Shift on Cropland Share: Fixed Effects Comparison

	(1)	(2)	(3)
Cold days (z $\leq$ -1)	0.0834***	0.0525***	0.0891***
	(0.0090)	(0.0095)	(0.0125)
Hot days (z $\geq$ 1)	0.0606***	0.0438***	0.0651***
	(0.0102)	(0.0102)	(0.0141)
Wasserstein Temp (lag)	-1.5929***	-1.4141***	-1.7658***
	(0.2731)	(0.2428)	(0.2778)
Wasserstein Precip (lag)	0.0036	-0.0008	0.0168
	(0.0128)	(0.0151)	(0.0154)
SPI (planting season)	-0.0895***	-0.1340***	-0.1404***
	(0.0215)	(0.0231)	(0.0265)
Fixed Effects:			
Pixel	Yes	Yes	Yes
Year	Yes	Yes	Yes
ERS Region × Year	No	Yes	No
State × Year	No	No	Yes
Observations	102,645,526	102,645,526	102,645,526
R^2 (within)	0.0016	0.0007	0.0009
Clusters (counties)	3,106	3,106	3,106

Notes: Standard errors clustered at county level in parentheses.
Cold days = days with z-score $\leq$ -1; Hot days = days with z-score $\geq$ 1 during planting season.
* p<0.10, ** p<0.05, *** p<0.01

Table 2: Two-Stage Wasserstein Decomposition

	Coefficient	Std. Error
Panel A: First Stage		
(Wasserstein ∼ Mean Shift)		
Mean Temperature Shift	0.8161***	(0.0108)
First-stage R^2	0.8695	
Observations	102,645,526	
Panel B: Second Stage		
(Cropland ∼ Mean Shift + Residual)		
Mean Temperature Shift	-1.6156***	(0.4439)
Wasserstein Residual	1.6182	(1.4365)
Wasserstein Precip (lag)	0.0282*	(0.0158)
SPI (planting season)	-0.1440***	(0.0271)
Extreme Cold Days	0.1067***	(0.0161)
Extreme Heat Days	0.0267**	(0.0125)
Observations	102,645,526	
R^2 (within)	0.0008	
Clusters (counties)	3,106	

Notes: Cluster-robust standard errors (county level) in parentheses.
First stage regresses Wasserstein on mean shift with pixel and year FE.
Second stage includes pixel, year, and state×year FE.
Wasserstein residual = distributional change beyond mean shift.
* $p<0.10$, ** $p<0.05$, *** $p<0.01$