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Abstract

We combine 2008-2023 county-level yield data with 30-meter crop classification imagery to test whether crop diversity mitigates yield losses from weather shocks. Diversity is measured with the exponential Shannon index, capturing county-level species richness and evenness as the effective number of crops. Two-way fixed-effects regressions replicate standard nonlinear damages from extreme heat and precipitation, but show that each additional effective crop attenuates heat impacts for corn and soybean and moderates winter wheat losses in unusually wet years. Resilience benefits are concentrated in rainfed counties, where irrigation offers limited protection, indicating that diversification can complement water-based adaptation to climate change.

Keywords: Adaptation; Agriculture; Crop Diversity; Weather shocks; Climate change; Extreme temperatures; Drought

JEL Codes: Q10; Q15; Q54; Q57; C23.

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1 Introduction

Over recent decades, U.S. land allocation has become increasingly specialized: more than half of the national land area is in agricultural use, and about two-thirds of harvested cropland is devoted to corn, soybeans, and winter wheat (USDA NASS, 2017). Over the same period, extreme heat and moisture shocks have intensified, generating well-documented nonlinear yield losses (Schlenker and Roberts, 2009; Carleton and Hsiang, 2016) and growing yield volatility (Renard et al., 2023). While mitigation requires global coordination, adaptation is largely local. Adjusting the crop mix is a private margin that can deliver agronomic services (Di Falco and Chavas, 2008; Landis, 2017; Nelson and Burchfield, 2021) and complement resource intensive strategies such as irrigation (Scanlon et al., 2012).[1]. We ask whether crop diversity can serve as an adaptation margin by reducing the marginal damage from weather shocks and, if so, where those gains are concentrated.

To address these questions, we leverage 2008 to 2023 30-meter Cropland Data Layer imagery from the U.S. Department of Agriculture (2024a) together with county-year yield data for corn, soybean, and winter wheat (USDA NASS, 2024b). We construct an annual county-level measure of crop diversity based on the exponential Shannon index, which captures both the richness of the crop mix and the evenness of cropland shares as the effective number of crops.[2] We then interact this diversity index with plausibly exogenous within-county year-to-year temperature and precipitation shocks in two-way fixed-effects regressions. This design treats short run weather variation as quasi-random (e.g., Deschênes and Greenstone, 2007; Dell et al., 2014; Auffhammer et al., 2013; Mérel and Gammans, 2021) and allows us to quantify how crop diversification mediates the response of U.S. crop yields to heat and precipitation shocks.

Our specification follows the climate-economics literature. Temperature shocks are measured as cumulative heat exposure over the growing season using growing degree hours (GDH) and harmful degree hours (HDH) (e.g. Schlenker and Roberts, 2009; Carleton and Hsiang,

[1] Ecological research shows that diversity enhances key ecosystem services (Cardinale et al., 2012), including pollination, pest control, water retention, and nutrient cycling (Swinton et al., 2007; Nelson and Burchfield, 2021) These services are crucial for plant resilience to stressors such as heat waves and precipitation variability.

[2] A one-unit increase in this index corresponds to cultivating one additional crop in equal proportion to the others. We later consider richness and Simpson indices as alternative diversity measures, which differ in their sensitivity to rare species. See section 2.1.

2016), and total growing season precipitation is summarized by county-specific terciles (Burgess et al., 2017).[3] Consistent with existing studies, extreme heat has a large negative effect on yields: a 1,000-hour increase in HDH (about one standard deviation) reduces corn, soybean and winter wheat yields by 14.1%, 19.4%, and 11.8%, respectively ($p<0.01$). Rainfall effects are concave: years in the lowest tercile cut corn and soybean yields by 3.3% and 4.2% ($p<0.01$), while the highest tercile lowers corn and wheat yields by 1.0% and 1.8% ($p<0.01$).

We then quantify resilience by allowing the marginal effect of each weather variable to vary with crop diversity through interaction terms. The associated coefficients measure how a one-unit increase in the exponential Shannon index affects the yield impact associated with a given weather shock. The results show that diversity partially offsets the damage from extreme heat and low precipitation for corn and soybean. Quantitatively, a one-unit increase in diversity reduces the HDH effect by about 8.4% for corn and 6.1% for soybean ($p<0.01$). Under drought (first rainfall tercile), the resilience effect of diversity corresponds to a 15.2% ($p<0.05$) offset of the main effect for corn and 9.5% ($p<0.10$) for soybean. For winter wheat, the only robust resilience effect appears under high rainfall, where diversity attenuates yield declines by around 30% ($p<0.10$).

To account for heterogeneity in weather impacts and resilience, we estimate the model separately by irrigation status for corn and winter wheat.[4] Three key findings emerge. First, irrigation mitigates the direct effect of extreme heat on corn yields, but the diversity interaction is larger in rainfed counties: a one-unit increase of diversity offsets about 5% of the HDH effect for corn ($p<0.1$) and about 23% for winter wheat ($p<0.1$). Second, in rainfed regions, diversity mitigates both low and high rainfall shocks to corn yields: a one-unit increase in diversity offsets about 37% of the low rainfall loss ($p<0.01$) and 53% of the high rainfall loss ($p<0.05$). Third, for winter wheat extreme heat impacts tend to be larger in irrigated counties, although we find some evidence that diversity offsets extreme heat yield losses for rainfed winter wheat. A one-unit increase in diversity offses negative impacts of HDH by around 22% ($p<0.1$). Overall, this indicates a complementarity between irrigation and diversity as an adaptation strategy

[3] GDH captures heat accumulation up to a temperature threshold that is detrimental to crop growth, while HDH measures exposure to temperatures exceeding that threshold. Precipitation is summed over the growing season and classified into terciles using each county's historical distribution during the study period.

[4] For soybean there is virtually no irrigated cropland area, so it is not considered in this analysis.

to weather shocks in the context of climate change.

We also extend the analysis to alternative diversity indices. Species richness (a count of crops) provides similar results for corn: interactions with HDH and low rainfall shocks are positive, indicating that diversity offsets heat and drought losses. Results based on the Simpson index, which instead captures dominance or concentration, confirm these findings. For soybean and winter wheat, interaction estimates using richness and Simpson are smaller and less precise than with Shannon. These patterns suggests that resilience effects are primarily tied to evenness in the crop mix (captured by Shannon), rather than to the simple number of species or to acreage concentration. Lastly, we also re-estimate the model based on landscape diversity, which includes non-cultivated vegetation. We find that crop-based diversity drives the main resilience effects and average yield associations, although landscape diversity also contributes.

Lastly, we run a number of robustness checks. First, we consider the concern that diversity measure is endogenous. We re-estimate our main specification using lagged diversity values and fix diversity at its first observed value. Our results show that estimates for interaction terms are consistent across specification, whereas direct effects of diversity on yields are sensitive to the use of lagged values, suggesting that these estimates should interpreted as descriptive rather than causal. Second, we include quadratic time trends in the analysis, and confirm robustness of our main results. Overall, these checks reinforce the main resilience results discussed above, namely that diversity provides resilience benefits for corn and soybean in the presence of extreme temperature shocks, and for winter wheat in unusually wet years.

Our study is related to several strands of literature. First, it adds to the growing economics literature on the value of crop diversity in agricultural production and ultimately in farmer revenues (Di Falco, 2012; Sodjahin et al., 2025; Nicita and Mendelsohn, 2024; Burchfield et al., 2019). While these studies focus on understanding how regional and farm level crop mix affects production, they do not account for the interaction with climate stress. To the best of our knowledge, we are the first to use highly disaggregated data to examine the yield benefits of crop diversity in the context of climate change.

However, a number of studies investigate the potential of crop diversity to buffer against weather shocks either in very specific and local agroecosystems or at a very aggregated level. Based on Italian data, Di Falco and Chavas (2008) find that increased crop diversity strengthens

the resilience of the ecosystem and helps counteract the detrimental effects of decreased precipitation and droughts on wheat yield. Auffhammer and Carleton (2018) use administrative data for the production of 20 crops and find that Indian districts with a more diverse crop mix are more resilient to droughts. Similarly, Renard et al. (2023) uses national data spanning 58 years and concludes that diversifying crop varieties within countries can temper the negative consequences of droughts and higher temperatures on farm output. Relative to these study, we provide a systematic investigation of both temperature and precipitation shocks and include diversity measure based on land use imagery.

Second, our work relates to a literature on how crop diversification might be a suitable adaptation strategy to cope with environmental risk, especially for farmers in developing countries (e.g. Amare and Balana, 2023; Bozzola and Smale, 2020; Di Falco and Chavas, 2009; Di Falco et al., 2010; Ferry and de Montalembert, 2025). For example, Bozzola and Smale (2020) find that smallholder farmers in Kenya respond to past climate shocks by increasing crop diversification, which enhances income and reduces risk. Both crop richness and evenness are associated with lower income variability, particularly for vulnerable farmers, while crop specialization increases risk exposure.

Third, our findings contribute to a broader literature on climate change and its implication for agricultural production (e.g., Dell et al., 2014) by providing novel evidence on the relationship between weather variables and crop yields. The association between extreme weather events and agricultural production is documented in numerous studies, including those by Schlenker and Roberts (2009), Schauberger et al. (2017), Jayachandran (2006), Iizumi and Ramankutty (2015), Fezzi and Bateman (2015), Ochieng et al. (2016), Chen et al. (2016), among others. We add to this literature by discussing crop diversity in the context of alternative adaptation strategies, including irrigation.

The remainder of this paper is organized as follows. Section 2 provides information on the data and the empirical strategy used in the analysis. Section 3 reports our main results and robustness checks. Finally, section 4 briefly discusses our results and concludes.

2 Empirical strategy

This section explains our empirical strategy to identify the extent to which local crop diversity buffers yields against weather shocks. We first describe the county-level dataset we assemble and the construction of our diversity index. We then lay out the econometric model and identification strategy that exploits within-county weather variation to estimate the resilience effects of diversity.

2.1 Data

We assemble a panel dataset for all 3,108 counties in the contiguous United States over 2008-2023. The dataset combines (i) county-level yields for corn, soybean, and winter wheat, (ii) daily weather variables aggregated to growing season harmful and growing degree hours as well as tercile indicators for precipitation, (iii) several measures of crop diversity, and (iv) the share of cropland under irrigation. Table 1 provides summary statistics by crop. In the following, we detail data sources and the construction of each variable.

Agricultural yields. County-level agricultural production, acreage and yield figures are taken from the USDA NASS database (USDA NASS, 2024b). The data are derived from quarterly and annual farm surveys complemented by administrative checks. We focus on the three major U.S. field crops: corn, soybean, and winter wheat. These three crops together accounted for around 65% of total harvested cropland in 2017 (USDA NASS, 2017). For each crop in each county-year, yield is calculated as production divided by harvested acreage and is measured in bushels per acre (bu/acre). Note that winter wheat is planted in year t-1 and harvested in year t, so that the first year of observation is 2009. Table 1 shows the large spatial and temporal variability in yields corn ranges from roughly 10 to 277 bu/acre, soybean from 3.6 to 80 bu/acre, and winter wheat from 6 to 155 bu/acre, with the highest values concentrated in the Midwestern "Corn Belt" and other high-productivity zones.

Weather variables. We retrieve hourly air temperature data from ERA5 reanalysis at 0.25°x 0.25°(around 27km by 27km) resolution (Hersbach et al., 2024). Daily precipitation data are from PRISM Climate Group, Oregon State University (2024) and recovered at a 4km by 4km resolution. For each crop, we obtain cumulative exposure to heat and water by temporally ag-

Table 1: Summary statistics for corn, soybean and winter wheat

Variable	Mean	SD	Min	Max
Corn (N = 24,371)				
Yields	147.01	39.54	10.40	277.10
GDH (in 10,000)	5.09	0.82	1.61	7.99
HDH (in 1,000)	1.22	1.28	0	17.11
Crop diversity	3.97	1.50	1.18	16.03
Irrigation share	0.22	0.30	0	1.00
Soybean (N = 19,158)				
Yields	45.05	10.83	3.60	80.40
GDH (in 10,000)	4.63	1.03	0	6.83
HDH (in 1,000)	0.68	0.77	0	8.28
Crop diversity	3.99	1.41	1.36	10.85
Irrigation share	<0.01	0.002	0	0.27
Winter Wheat (N=11,087)				
Yields	58.85	16.81	6.20	154.50
GDH (in 10,000)	6.90	1.00	3.05	11.75
HDH (in 1,000)	0.26	0.31	0	3.76
Crop diversity	4.12	1.52	1.31	16.03
Irrigation share	0.14	0.24	0	1.00

Notes: N is county-year observations. Yields are reported in bushels per acre. Growing degree hours (GDH) is measured in 10,000°C-hours, harmful degree hours (HDH) is in 1,000°C-hours. The diversity index is the exponential of the Shannon index, so the mean is the effective number of crops (see text). The irrigation share is representative of the 2015 irrigation and thus constant over the study period. For soybean there is virtually no irrigated cropland area.

gregating weather variables over the respective county boundaries and growing season calendar following the state-level crop calendar given by Sacks et al. (2010).[5]

Temperature indices follow Schlenker et al. (2006) and capture cumulative heat exposure split into GDH and HDH. This parsimoniously captures non-linearities identified in the literature documenting a yield-climate relationship (e.g. Schlenker and Roberts, 2009). Formally, GDH and HDH indices are defined as follows:

$$GDH_{it}^{c} = \sum_{h=1}^{n_i^c} (\min(T_{it}^{h}, \tau_{high}) - \tau_{low}) \mathbf{1}(T_{it}^{h} \geq \tau_{low}),$$

[5] Sacks et al. (2010) provide a state-specific calendar for the growing season of different crops. We use the median planting and harvesting dates in each state. Therefore, the number of hours in a growing season, n_i^c, is county and crop-dependent. However, this calendar is fixed in time, and we therefore abstract from any calendar shifts over 2008-2023.

$$HDH_{it}^{c} = \sum_{h=1}^{n_i^c} (T_{it}^{h} - \tau_{high}) \mathbf{1}(T_{it}^{h} \geq \tau_{high})$$

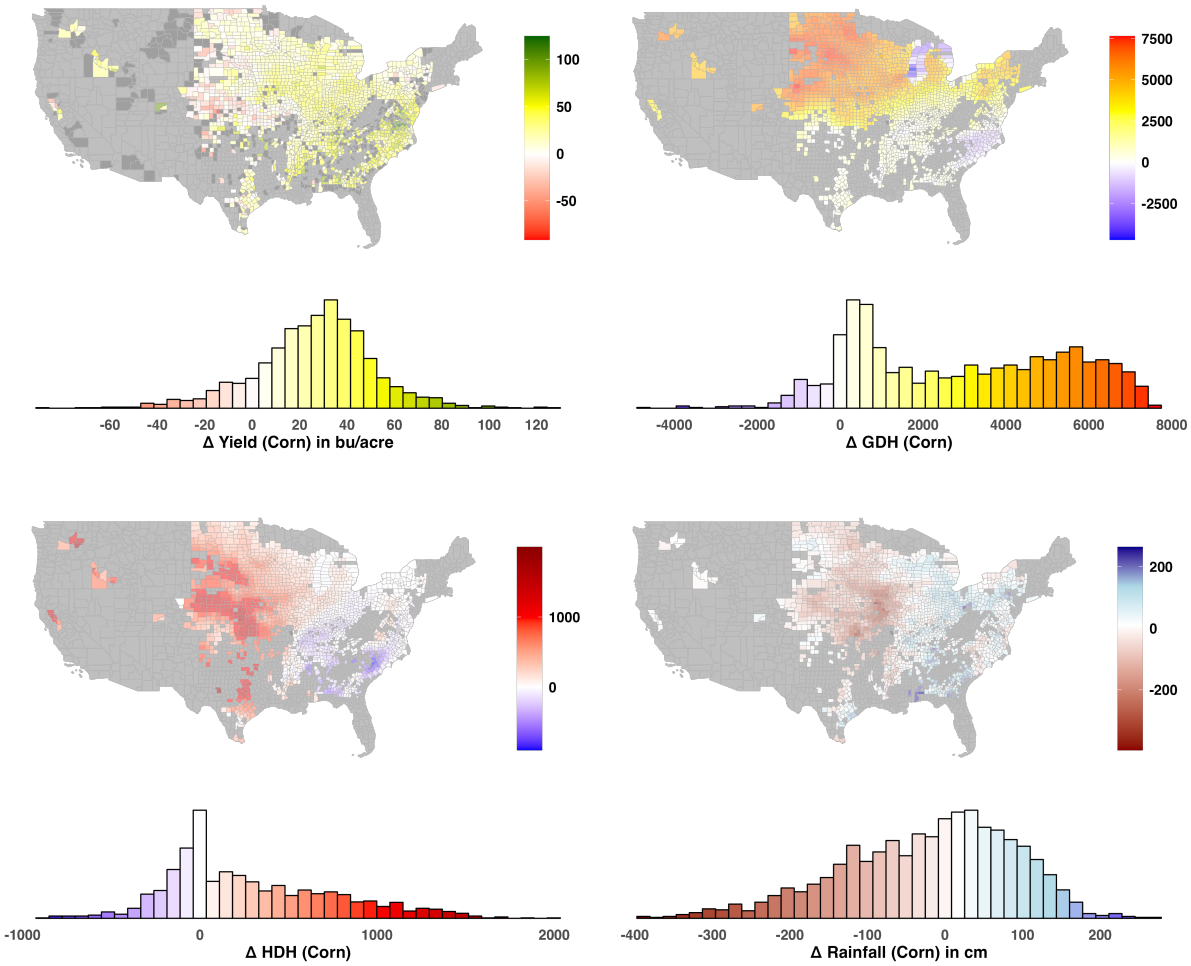
where n_i^c is the total number of hours in the respective growing season of crop c in county i, T_{it}^h is hourly temperature(°C) in county i and year t, and τ_{low} and τ_{high} are thresholds defined for each crop: τ_{low} is set to 8°C for corn and soybean, 0°C for winter wheat (Aragón et al., 2021; Burchfield et al., 2019); τ_{high} is 29°C for corn, 30°C for soybean and winter wheat (Schlenker and Roberts, 2009; Burchfield et al., 2019). In the regressions, GDH is expressed in 10,000°C-hours, and HDH is in 1,000°C-hours.

Precipitation indicators are based on total growing season rainfall in county i during year t, P_{it}^c, and compared with the county's own historical distribution (2008-2023). Following Burgess et al. (2017), we create tercile dummies $\mathbf{1}\{\mathrm{P}_{it}^c \in \text{tercile } k\}$ corresponding to low / high rainfall and omit the middle tercile to capture "normal" conditions. We model rainfall as the sum of daily precipitation over the growing season, rather than high frequency extremes, because cumulative rainfall better accounts for potential water storage capacity that crops experience. Moreover, using terciles (rather than absolute thresholds) focuses on deviations from the local conditions to which farming practices are adapted, and balances statistical power with tractability.

Figure 1 illustrates county-level changes between 2008-2010 and 2021-2023 (three year means at each endpoint) in corn yields and in the three weather variables used in the regression. Each map is paired with a county histogram to show the distribution of changes. We observe that most corn-growing counties experienced an increase in GDH, with few exceptions in counties located in the Grand Lake region and the south eastern Coastal Plain. However, we also observe a rise in HDH and a decrease in growing season rainfall in some areas. Similar figures for soybean and winter wheat are displayed in the Appendix A1 and A2 respectively, indicating the same broad warming pattern. The main difference concerns extreme heat: Table 1 shows that corn is the most affected crop with an average of 1,200 degree hours above 29°C. In contrast, winter wheat experiences the least heat exposure because its growing season occurs outside of the summer months.

Crop Diversity. We measure crop diversity with the USDA Cropland Data Layer, which classifies 30 meter by 30 meter pixels into more than one hundred crop and land cover classes

Figure 1: County-level changes in corn yield, growing and harmful degree hours, and growing season rainfall, 2008-2023



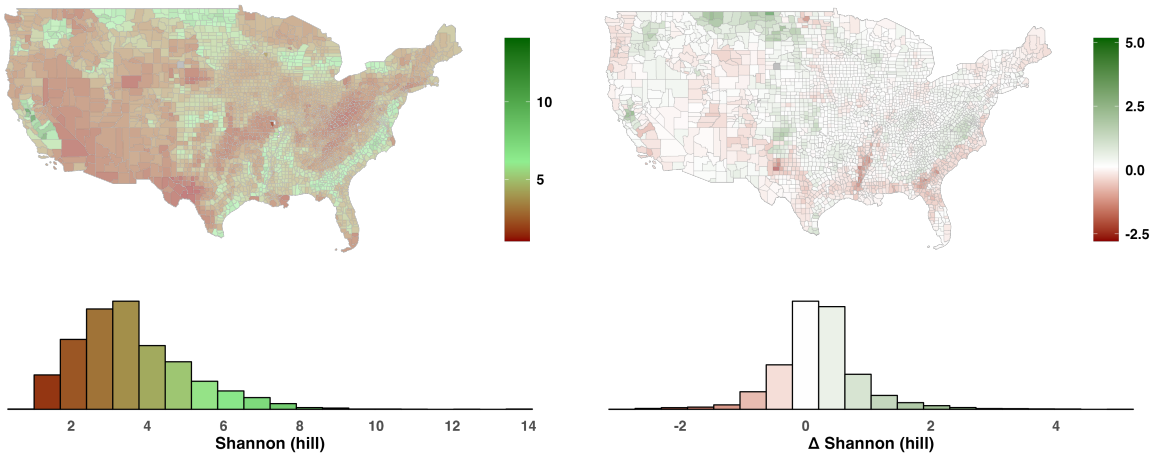
Notes: This figure reports differences in corn yield and weather variables between 2008-2010 and 2021-2023 three year averages for all counties with non-suppressed observations in at least one year of each window. Histograms below the maps give the distribution of county changes. Upper left panel shows difference in corn yield in bu/acre. The upper right panel displays difference in growing degree hours (in 10,000°C-hours) and the lower left panel shows difference in harmful degree hours (in 1,000°C-hours). The lower right panel presents the difference in cumulative growing season rainfall (cm).

each year (USDA NASS, 2024a). For each county i and year t, we follow Aramburu Merlos and Hijmans (2020) and compute a diversity index D_{it} defined as the exponential of the Shannon entropy index:

$$D_{it} = \exp\left(-\sum_{c=1}^{S_{it}}(p_{ict}\ln p_{ict})\right)$$

where p_{ict} is the share of cropland area covered with crop c in county i and year t, and S_{it} is

Figure 2: Spatial distribution of Shannon crop diversity



Notes: This figure reports the geographical distribution of the Shannon crop diversity index for the period 2008-2023. The left panel shows the average value of the exponential Shannon index for each county. The right panel displays the change in that index between 2008-2010 and 2021-2023 three year averages. Histograms below each map give the distribution of county averages and changes, respectively.

the total number of crop species in the county.[6] The exponential transformation of the Shannon index delivers "effective number of species" or "hill number". It is the equivalent number of equally common species that would be needed to get the same diversity value as the actual dataset. A higher value of D_{it} thus indicates both richer and more even portfolio of crops.[7]

Figure 2 maps the geographical distribution of the exponential Shannon index of crop diversity. The left panel displays the county mean for 2008-2023, revealing significant variation, with high diversity regions primarily located in the North, the Southeast, and California. In contrast, the Western regions and most of the Northeast exhibit relatively low levels of crop diversity. This latter area is characterized by extensive grain crop agriculture, particularly in the Corn and Soybean Belt. The right panel plots the change in the index between 2008-2010 and

[6] S_{it} encompasses 107 cultivated crops such as corn, cotton, rice, various fruits and vegetables. Cropland area refers to the county land area after removing land types that are unrelated to vegetation such as developed (concrete), water, or barren. We exclude these items for the calculation of the index and list them in the appendix Table B1. Moreover, we do not consider temporal diversity such as crop rotation, but we account for double cropping within a growing season and treat it as a separate items in the calculation of the diversity index. In a subsequent step, we also include the 12 non-cultivated crop categories, which include forest, wetlands, grass or pasture lands. We come back to this below.

[7] Note that $D_{it} = n$ would indicate a situation in which the county would have the same diversity as a hypothetical field planted evenly to n crops.

2021-2023. Over the 15 year study period, crop diversity has remained relatively stable in most counties, though there has been a notable increase in the North. Table 1 indicate an average of about 4 crop equivalent per county. However, we also observe a wide range, with some counties exhibiting monoculture practices, while others exhibit up to 16 different crops in terms of effective species.

We also consider two alternative indices drawn from Hill's diversity continuum (Hill, 1973). First, we consider species richness as S_{it}, which is the number of cultivated crop species in county i and year t. Richness is sensitive to any crop species present in a given area, regardless of its relative importance. Second, we use the Simpson index, which is defined as:

$$\mathrm{D}_{it} = \frac{1}{\sum_{c=1}^{S_{it}} p_{ict}^2}.$$

Simpson gives more weight to abundant species and down weights rare ones. Whittaker (1965) suggests one should interpret this measure as a dominance or concentration. Our main analysis relies on the Shannon index because it lies between these two extremes, balancing sensitivity to rare crops (richness) with sensitivity to evenness (Simpson) (Di Falco and Chavas, 2008).

Figure A3 shows the geographical distribution of the long run average and the 2008-2023 change in richness and Simpson indices. The richness map shows highly diverse agricultural lands in the Central Valley of California (large variety of nuts, fruits, and vegetables) whereas the Corn and Soybean Belt in the central United States exhibits much lower richness. The Simpson index instead rises when cropland is spread more evenly across the species that are present. Values are highest in eastern counties, suggesting that few crop species are cultivated, but in even proportions. One might also note that richness increased in almost all counties between 2008 and 2023, whereas the Simpson index moves little.

Irrigation. County irrigation status is derived from GAEZ +2015 dataset (Frolking et al., 2020), which reports 2015 crop specific irrigated and rainfed areas on a 5 arc minute (approx. 3km) resolution. Grid cells are aggregated to county boundaries, and following Schauberger et al. (2017) we classify counties based on the share of irrigated area for each crop. Specifically, a county is irrigated if its irrigation share ≥ 0.75, rainfed when its irrigation share ≤ 0.1, and mixed otherwise. Based on these thresholds, Table 1 shows that about 22% of U.S. corn land is irrigated, compared to 14% for winter wheat, whereas soybeans only has five counties that

exceed the 10% threshold.[8] Appendix Figure A4 maps the resulting irrigation categories for each crop.

2.2 Econometric estimation

We aim to estimate the causal impact of weather shocks on county-level yields of corn, soybean, and winter wheat, and to assess how crop diversity moderates those impacts. Our strategy exploits a panel of U.S. counties and we estimate two-way fixed effects regressions that absorb both county and year heterogeneity (Deschênes and Greenstone, 2007; Blanc and Schlenker, 2017). Following Carleton and Hsiang (2016), causal identification comes from within-county, year-to-year variation in weather, which is widely regarded as quasi-random with respect to local economic conditions (see also Dell et al., 2014; Auffhammer and Carleton, 2018). Under this assumption weather fluctuations are plausibly exogenous and coefficients on the weather variables can be interpreted as causal.

Formally, for each crop c we start by estimating the following regression:

$$log(Y_{it}^c) = \beta^{c'} \mathbf{W_{it}^c} + \alpha_i^c + \delta_t^c + \epsilon_{it}^c \,, \tag{1}$$

where Y_{it}^c denotes yield for crop c in county i and year t, $\mathbf{W_{it}^c}$ is a vector of our four weather variables: GDH, HDH, and indicators for low and high rainfall terciles. Including both temperature and precipitation terms limits potential omitted variable bias (Auffhammer et al., 2013), and later allows us to separately quantify diversity-temperature and diversity-precipitation interactions, see below. Equation (1) also includes county fixed effects α_i^c and year fixed effects δ_t^c. Standard errors are clustered at the county level to account for serial correlation in the error term ϵ_{it}^c.

In equation (1), the vector β^c quantify causal semi-elasticities of yields with respect to deviation in temperatures and precipitations during the growing season. The implied relationship is:

$$\beta^{c'} \mathbf{W_{it}^c} = \beta_1^c GDH_{it}^c + \beta_2^c HDH_{it}^c + \beta_3^c RAINlow_{it}^c + \beta_4^c RAINhigh_{it}^c \,,$$

[8] These five counties are all adjacent to the border with Mexico. From table 1, we know that the county with the highest irrigation share for which yield data is available has an irrigation share of 27%.

so that, for example, β_2^c gives the approximate percentage change in yield associated with 1,000 additional harmful degree hours. This strategy offers the advantage of parsimony, requiring the estimation of only a few coefficients, while still capturing the underlying nonlinear yield-weather relationship. Mérel and Gammans (2021) show that in large spatial panels (such as counties in contiguous United States) where most temperature variation is cross-sectional rather than time-series, coefficients on degree hour measures mainly reflect the long run climatic gradient. The same dominance cross-sectional variability is not observed for precipitation, which exhibits greater year on year variability within counties.

Based on this specification, we test whether crop diversity modulates the yield response to whether shocks, a diversity resilience effect. In particular, we extend equation (1) by adding the Shannon index D_{it} and its interactions with the four weather variables:

$$log(Y_{it}^c) = \beta^{c'}\mathbf{W_{it}^c} + \gamma^{c'}\mathbf{W_{it}^c}D_{it} + \phi^c D_{it} + \alpha_i^c + \delta_t^c + \epsilon_{it}^c\,, \tag{2}$$

where elements in the vector of interest γ^c measure resilience: each element shows how a one-unit increase in the diversity index changes the yield semi-elasticity with respect to a given weather variable. The coefficient ϕ^c captures the direct yield effect of a unit increase in the diversity index. Note that all regressors are centered at their respective means, so that the main effect coefficients are estimated at representative growing season conditions. As in equation (1), we include county and year fixed effects and cluster standard errors at the county level.

We further use equation (2) to document crop-diversity resilience along three dimensions. First, for corn and winter wheat we estimate the model separately for rainfed (<10% irrigated cropland), mixed (10–75%), and irrigated (>75%) counties. Soybean is excluded from this analysis because fewer than 1% of soybean growing counties meet the 10 percent irrigation threshold. Second, beyond the baseline Shannon index which accounts for both species richness and evenness, we re-estimate equation (2) with two alternative diversity indices: (i) species richness, a simple count of crop species, and (ii) the Simpson index, which increases as cropland area becomes concentrated in a few crops. This implies that the interaction terms with richness indicates how adding one more crop species changes the yield response to a weather shock, whereas the interactions with Simpson capture how increased concentration and lower evenness modifies that response, reversing the sign capturing resilience of increased diversity. Third, we

extend the calculation of the index to include both cultivated and non-cultivated items listed in the Cropland Data Layer (USDA NASS, 2024a). This accounts for the fact that yields may depend on the composition of the entire landscape rather than on the crop mix alone (Nelson and Burchfield, 2021). Comparing results for crop-based and landscape-based Shannon indices provides evidence about the channels for yield and resilience benefits of diversity.[9]

Importantly, one potential concern with identification is that crop diversity D_{it} may be chosen in response to unobserved yield determinants, so the main effect coefficient ϕ^c cannot be interpreted causally. Following the argument in Angrist and Krueger (1999), however, the interaction $\mathbf{W_{it}^c} D_{it}$ can still be treated as exogenous because the vector $\mathbf{W_{it}^c}$ is plausibly random once county and year fixed effects are controlled for.[10] This allows us to interpret the interaction coefficients γ^c as the causal effect of crop diversity on the yield response to weather shocks, even though ϕ^c need not be causal.

Existing studies suggest that U.S. farmers adjust crop portfolios only slowly, if at all, in response to weather variations. Burke and Emerick (2016) find negligible adaptation in either crop choice or input use, and Annan and Schlenker (2015) show that federal crop insurance, which covers around 80% of corn and soybean cropland, further reduces incentives to reallocate land in response to weather shocks. These institutional features mitigate concerns that our diversity measure is endogenous. We address the issue with two robustness checks. First, we re-estimate equation (2) using lagged diversity values ($D_{i,t-1}$), allowing diversity to influence yields only through pre-determined agronomic channels (e.g., soil quality or water retention). Second, we fix diversity at its first observed value, namely $D_{i,2008}$ for corn and soybean, and $D_{i,2009}$ for winter wheat to account for the growing season that spans two calendar years. This eliminates any contemporaneous link between $D_{i,2008/2009}$ and the error term. Consistency of the coefficients across these specifications would strengthen the claim that the main effect of diversity can be interpreted as a causal relationship.

[9] We note that a limitation of using the Cropland Data Layer (USDA NASS, 2024a) for assessing landscape diversity is that non-crop classes are recorded in broad categories (e.g., four types of forests), whereas crop classes are reported at a higher resolution. We provide a list of all non-cultivated categories in Table B2 of the Appendix.

[10] Specifically, we assume that after accounting for crop diversity (D_{it}) and fixed effects (α_i and δ_t), the weather variables ($\mathbf{W_{it}}$) do not directly influence the unobserved determinants of yields. Formally,

$$\mathbb{E}[\epsilon_{it} \mid \mathbf{W_{it}}, D_{it}, \alpha_i, \delta_t] = 0$$

Thus any remaining variation in yields (ϵ_{it}) is not systematically related to the weather variables.

Lastly, we re-estimate equation (2) with quadratic time trends to capture unobserved effects associated with an upward trend in yields over time. We use three alternative approaches to capture regional trends in a flexible manner: (i) as a common quadratic trend across all counties, (ii) state-specific quadratic trends, or (iii) county-specific quadratic trends. These alternative specifications flexibly control for smooth nonlinear, unobserved factors at different spatial scales, such as technological progress (e.g. better seeds or fertilizers) or shifts in farmer behavior. However, we note that county-level quadratic time trends imply a risk of overfitting and absorbing economically meaningful variation, so that results from that specification should be interpreted with caution.

3 Results

This section reports the empirical results. First, we quantify the impact of weather shocks on crop yields and document how increased crop diversity influences this relationship. Second, we investigate heterogeneity effects across irrigation status. Third, we report estimates using alternative diversity indices. Finally, we compare the effects of crop diversity with those of landscape compositional diversity. We close with robustness checks.

3.1 Main results

Table 2 presents the results for OLS estimation of equation (1) in the odd-numbered columns and equation (2) in the even-numbered columns for the three crops analyzed. The outcome variable is the logarithm of crop yields (in bushels per acre), and we capture the impact of growing temperatures with GDH over the growing season (in 10,000) and harmful temperatures with HDH (in 1,000), both measured over the local growing season for each crop. The impact of low / high rainfall during the growing season are represented by two indicator variables capturing bottom and top precipitation terciles. Lastly, crop diversity is measured by the exponential Shannon entropy index and interacted with measures of temperatures and rainfall. All specifications further include county and year fixed effects, and standard errors clustered at the county-level are reported in parentheses.

Results from the benchmark specifications (odd columns) are highly consistent with the

Table 2: Yields, weather shocks and crop diversity

	Corn		Soybean		Winter wheat	
	(1)	(2)	(3)	(4)	(5)	(6)
GDH	0.020**	0.020**	0.003	0.006	-0.062***	-0.057***
	(0.009)	(0.009)	(0.0a09)	(0.009)	(0.009)	(0.009)
× Shannon		0.009**		-0.002		-0.010***
		(0.004)		(0.003)		(0.003)
HDH	-0.141***	-0.143***	-0.194***	-0.196***	-0.118***	-0.123***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.013)	(0.014)
× Shannon		0.012***		0.012***		0.002
		(0.003)		(0.003)		(0.008)
Low rainfall	-0.033***	-0.032***	-0.042***	-0.041***	0.008*	0.008*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)
× Shannon		0.005**		0.004*		0.003
		(0.002)		(0.002)		(0.003)
High rainfall	-0.010***	-0.010***	0.008***	0.007***	-0.018***	-0.018***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
× Shannon		0.00001		-0.00007		0.006*
		(0.002)		(0.002)		(0.003)
Shannon		0.021***		0.005		0.017***
		(0.005)		(0.004)		(0.006)
Observations	24,371	24,371	19,158	19,158	11,087	11,087
Counties	2,127	2,127	1,716	1,716	1,471	1,471
R^2	0.733	0.735	0.768	0.732	0.742	0.744
Within R^2	0.149	0.159	0.245	0.249	0.027	0.031

Notes: OLS regressions reported with the log of crop yields in bushels per acre as the dependent variable. GDH measure growing degree hour (in 10,000) and HDH are harmful degree hour (in 1,000). Low rainfall and High rainfall are indicator variables for the first and third terciles of the precipitation distribution, respectively. Diversity is measured with we use the exponential Shannon index (the effective number of crops). Independent variables are mean-centered. All specifications include county and year fixed effects. Standard errors are clustered at the county level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

existing literature that documents large, nonlinear temperature impacts to U.S. crops (e.g., Schlenker and Roberts, 2009; Schauberger et al., 2017). In particular, the coefficient on HDH is negative and highly significant for all three crops (p<0.01), implying that an increase of 1,000 in HDH (approx. 1 standard deviation), reduces yields by 14.1% for corn, 19.4% for soybeans and and 11.8% for winter wheat. An increase of moderate heat exposure (GDH) has a positive and statistically significant impact on corn yields, but no impact on soybean yields and a negative and statistically significant impact on wheat yields. While the result for winter wheat may seem surprising, it is consistent with the spring heat penalties reported in both Schauberger et al. (2017) and Tack et al. (2015). Results in Table 2 further show that years with relatively low

precipitations imply lower yields for corn (-3.3%, $p<0.01$) and soybean (-4.2%, $p<0.01$) relative to years with moderate rainfall. For winter wheat yield the effect of low rainfall is slightly positive and marginally significant (+0.8%, $p<0.1$). Years with relatively high rainfall imply lower yields for corn (-1%, $p<0.01$) and wheat (-1.8%, $p<0.01$), but higher yields for soybean (+0.8%, $p<0.01$). These coefficients are in line with the moisture stress gradients documented by Schlenker and Roberts (2009).

Columns 2, 4 and 6 of Table 2 quantify the effect of crop diversity (Shannon index) on yields and interactions with weather variables. The main effect coefficients are positive for corn and winter wheat and statistically insignificant for soybean. Quantitatively, a unit increase in the exponential Shannon index (corresponding to one additional crop cultivated evenly across the county) is associated with a 2.1% higher corn yield (column 2, $p<0.01$) and a 1.7% winter wheat yield (column 6, $p<0.01$). The soybean estimate (column 4) is near zero, in line with Burchfield et al. (2019). These effects are consistent with a general finding in the literature that average yield increases with crop diversity (Smale et al., 1998; Di Falco and Perrings, 2005). We note that the coefficients of the effects of weather variables on yields stay stable with the inclusion of the crop diversity variable, as none of the differences are statistically significant. This suggests that changes in diversity are not correlated with weather shocks, mitigating concerns of a potential bad control bias.

More interestingly, crop diversity tends to make yields more resilient to weather shocks. First, we find that it mitigates the negative impact of extreme temperatures. More specifically, a unit increase in the Shannon index reduces the negative yields effect of HDH by 1.2 pp ($p<0.01$) for corn (column 2) and soybean (column 4), offsetting 8.4% and 6.1% of the direct HDH impact, respectively. The corresponding interaction for winter wheat (column 6) is small and statistically insignificant. Second, we also find evidence of increased resilience against low and high levels of precipitation. For low rainfall, the coefficient for corn falls by 0.5pp ($p<0.05$) and 0.4 pp for soybean ($p<0.1$), implying offsets of 15% and 10%, respectively. The wheat interaction remains statistically insignificant. Under high rainfall, only winter wheat exhibits a significant interaction (-0.6 pp, $p<0.1$).

Table 3: Yields effects by irrigation status

	Corn			Winter wheat		
	Rainfed (1)	Mixed (2)	Irrigated (3)	Rainfed (4)	Mixed (5)	Irrigated (6)
GDH	0.078***	-0.089***	-0.059**	-0.021	-0.068***	-0.081***
	(0.013)	(0.015)	(0.028)	(0.013)	(0.017)	(0.021)
× Shannon	0.009	0.017***	0.002	-0.007**	-0.018***	-0.010
	(0.006)	(0.006)	(0.011)	(0.004)	(0.005)	(0.010)
HDH	-0.208***	-0.118***	-0.046***	-0.086***	-0.153***	-0.174***
	(0.009)	(0.006)	(0.010)	(0.018)	(0.022)	(0.033)
× Shannon	0.011*	0.008**	0.002	0.019*	0.006	-0.024
	(0.007)	(0.004)	(0.004)	(0.010)	(0.011)	(0.016)
Low rainfall	-0.028***	-0.036***	-0.028***	0.018***	-0.036***	-0.003
	(0.004)	(0.006)	(0.008)	(0.005)	(0.011)	(0.021)
× Shannon	0.010***	0.005	-0.003	0.004	0.007	0.021**
	(0.003)	(0.004)	(0.005)	(0.004)	(0.008)	(0.010)
High rainfall	-0.013***	-0.010*	-0.013*	-0.027***	0.019*	-0.003
	(0.003)	(0.005)	(0.008)	(0.004)	(0.010)	(0.020)
× Shannon	0.007**	-0.002	0.002	0.005	0.004	-0.015
	(0.003)	(0.004)	(0.005)	(0.003)	(0.006)	(0.009)
Shannon	0.042***	0.032***	-0.027***	0.023***	0.002	0.017
	(0.007)	(0.006)	(0.008)	(0.007)	(0.009)	(0.015)
Observations	14,058	7,484	2,781	7,814	2,689	584
Counties	1,119	680	315	971	398	102
R^2	0.741	0.736	0.829	0.722	0.729	0.858
Within R^2	0.214	0.181	0.076	0.019	0.07	0.166

Notes: OLS regressions reported with the log of crop yields in bushels per acre as the dependent variable. GDH measure growing degree hour (in 10,000) and HDH are harmful degree hour (in 1,000). Counties are classified as irrigated if the share of cultivated irrigated area is larger than 75%, rainfed if the irrigation share is smaller than 10%, and mixed in between. Low rainfall and High rainfall are indicator variables for the first and third terciles of the precipitation distribution, respectively. Diversity is measured with we use the exponential Shannon index (the effective number of crops). Independent variables are mean-centered. All specifications include county and year fixed effects. Standard errors are clustered at the county level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

3.2 Results by irrigation status

Table 3 reports results for the baseline model for corn and winter wheat separately by irrigation status.[11] A county is classified as *rainfed* when irrigated cropland accounts for less than 10% of total cropland area, *irrigated* when the share is larger than 75%, and *mixed* otherwise. All specifications replicate the presentation used in Table 2 and include county and year fixed effects. Standard errors are clustered at the county level and reported in parentheses.

[11] As discussed above, rainfed production dominates for corn and winter wheat, particularly in the Midwestern states. For soybean, production is rainfed with only a few exceptions, so that it is not considered here.

Starting with results for corn, we observe that HDH have a more pronounced negative impact in rainfed counties compared to irrigated counties. A 1,000 increase in HDH lowers corn yields by more than 20% ($p<0.01$), compared to around 12% ($p<0.01$) in mixed and 4.6% ($p<0.01$) in predominantly irrigated counties. In rainfed counties, an increase of the Shannon index by one unit offsets the negative impact of HDH by 1.1 pp ($p<0.1$) and in mixed counties by 0.8 pp ($p<0.05$). No significant resilience effect is estimated in irrigated counties. Crop diversity also mitigates the negative effect of rainfall shocks in rainfed regions. Specifically, while low rainfall years imply a decline in corn yields by 2.8% ($p<0.01$), a unit increase in crop diversity offsets that impact by 1 pp ($p<0.01$). Similarly, the loss of corn yields with high rainfall is 1.3% ($p<0.01$), and the corresponding offset is 0.7 pp ($p<0.05$). Lastly, the direct yield association with crop diversity is positive for rainfed and mixed counties (respectively 4.2% and 3.2%, $p<0.01$), but negative in irrigated counties (-2.7%, $p<0.01$). This observation aligns with findings for irrigated cereal systems in Pakistan reported in Smale et al. (1998).

For winter wheat, the pattern for extreme heat is reversed, as the marginal impact of HDH in rainfed counties is around -8.6% ($p<0.01$) and -17.4% ($p<0.01$) in irrigated counties. In rainfed counties, a unit increase in the Shannon index attenuates this loss by 1.9pp ($p<0.1$), whereas the interaction is not statistically significant in mixed and irrigated counties.[12] We further find that crop diversity contributes to drought resilience of winter wheat only when irrigation is present. In irrigated counties, low rainfall years do not affect average yields, but the interaction with the Shannon index is positive (2.1 pp, $p<0.05$), indicating that more even crop mixes raise yields under moisture deficits even with irrigation. Finally, the positive association between diversity and winter wheat yields is largest in rainfed counties, as a unit increase of Shannon is associated with a 2.3% ($p<0.01$) gain in yields, whereas the effects are smaller and not statistically significant for mixed and irrigated counties.

3.3 Alternative indices for crop diversity

This section explores results for equation (2) based on two alternative measures of crop diversity: county-level richness and the Simpson index, which measures concentration rather than

[12] It is important to approach these findings cautiously, as the sample size of counties using irrigation is relatively small, and the number of hours with harmful temperatures is also limited (refer to Table 1).

Table 4: Yields effects for alternative crop diversity indices

	Corn		Soybean		Winter wheat	
	Richness (1)	Simpson (2)	Richness (3)	Simpson (4)	Richness (5)	Simpson (6)
GDH	0.022**	0.022**	0.002	0.002	-0.063***	-0.061***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
× Index	0.0003	0.0005	0.0006*	-0.0005***	-0.0002	-0.0006
	(0.0005)	(0.0003)	(0.0003)	(0.0002)	(0.0004)	(0.0004)
HDH	-0.139***	-0.148***	-0.198***	-0.193***	-0.115***	-0.114***
	(0.005)	(0.005)	(0.007)	(0.006)	(0.013)	(0.013)
× Index	0.001***	-0.002***	-0.002***	0.0004	-0.0008	0.0004
	(0.0004)	(0.0003)	(0.0006)	(0.0003)	(0.0013)	(0.0013)
Low rainfall	-0.033***	-0.033***	-0.041***	-0.042***	0.007	0.007*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.004)
× Index	0.00009	-0.0005***	-0.0008**	-0.0006***	0.0008	0.001**
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0005)	(0.0004)
High rainfall	-0.010***	-0.011***	0.007***	0.008***	-0.017***	-0.018***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
× Index	-0.0006**	-0.0003	0.00003	0.0002	0.0002	-0.0008*
	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0005)	(0.0004)
Index	0.001***	-0.001***	0.001***	-0.0005*	0.002***	0.0002
	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0006)	(0.0007)
Observations	24,371	24,371	19,158	19,158	11,087	11,087
Counties	2,127	2,127	1,716	1,716	1,471	1,471
R^2	0.733	0.733	0.769	0.769	0.743	0.743
Within R^2	0.152	0.151	0.247	0.246	0.029	0.029

Notes: OLS regressions reported with the log of crop yields in bushels per acre as the dependent variable. GDH measure growing degree hour (in 10,000) and HDH are harmful degree hour (in 1,000). Low rainfall and High rainfall are indicator variables for the first and third terciles of the precipitation distribution, respectively. In odd columns the index refers to the richness index (species count), and in even columns we use the Simpson index (species concentration). Independent variables are mean-centered. All specifications include county and year fixed effects. Standard errors are clustered at the county level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

evenness. Table 4 reports the resulting OLS regression results for corn, soybean and winter wheat. All specifications include county and year fixed effects. Standard errors clustered at the county level appear in parentheses.

For corn interactions with extreme weather shocks show consistency with the resilience effects discussed for the Shannon index, but highlights the importance of how diversity is defined. Specifically, a higher species count (richness) continues to offset heat damage (positive HDH interaction), although the magnitude is an order of magnitude smaller than with Shannon. By contrast, greater concentration (higher Simpson) amplifies heat-stress losses (negative HDH interaction) and worsens the low-rainfall penalty, the opposite of what we observe for richness

and Shannon. This suggests that results in Table 2 (column 2) are mainly driven by evenness rather by the marginal crop. When diversity is measured as concentration (Simpson), counties that specialize more heavily in a smaller number of crops experience larger yield losses under heat and drought, reversing the protective pattern seen with the Shannon and richness indices.

For soybean and winter wheat, the resilience effects estimated for richness and Simpson indices diverge from those obtained with the Shannon index. For soybean, neither richness nor Simpson reproduces the positive offsets to extreme heat (HDH) and low rainfall shocks reported in Table 2, as coefficients are small and either insignificant or estimated with inconsistent signs. For winter wheat, the positive interaction for high rainfall shocks estimated with the Shannon index becomes insignificant when diversity is measured by richness and becomes negative when measured by Simpson, while all other interactions remain close to zero. These inconclusive results suggest that the resilience effects documented above are linked to evenness in the crop mix rather than to the simple number of species or to surface concentration, supporting our use of the Shannon index as the primary diversity measure.

Overall, we also confirm a direct association of diversity and yields for all crops, as measured by the main effects. Richness enters with a positive coefficient for all three crops, whereas the Simpson index yields negative coefficients for corn and soybean and an insignificant coefficient for winter wheat. While these direct estimates should be interpreted as correlational rather than causal, all indices suggest that yields rise with the number of crops and with evenness, but fall when a single crop dominates.

3.4 Landscape diversity

In Table 5, we report results comparing our baseline specification that uses a Shannon index calculated from cultivated crops only (reproduced from the even columns of Table 2) and a specification based on a Shanon index incorporating both cultivated and non-cultivated items listed in the Cropland Data Layer (USDA NASS, 2024a). The crop only diversity estimates appear in the left panel, the landscape diversity estimates in the right panel. All specifications include county and year fixed effects, and we report standard errors clustered at the county-level in parentheses.

Results suggest that the main effect of diversity on yields is stronger when considering crop

Table 5: Yields effects for crop vs. landscape diversity

	Crop diversity			Landscape diversity		
	Corn	Soybeans	Winter wheat	Corn	Soybeans	Winter wheat
	(1)	(2)	(3)	(4)	(5)	(6)
GDH	0.020**	0.006	-0.057***	0.019**	0.005	-0.059***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
× Shannon	0.009**	-0.002	-0.010***	0.009***	0.0003	-0.008***
	(0.004)	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)
HDH	-0.143***	-0.196***	-0.123***	-0.140***	-0.194***	-0.119***
	(0.005)	(0.006)	(0.014)	(0.005)	(0.006)	(0.014)
× Shannon	0.012***	0.012***	0.002	0.005*	0.007***	0.011
	(0.003)	(0.003)	(0.008)	(0.002)	(0.003)	(0.007)
Low rainfall	-0.032***	-0.041***	0.008*	-0.033***	-0.041***	0.008*
	(0.003)	(0.003)	(0.004)	(0.003)	(0.003)	(0.004)
× Shannon	0.005**	0.004*	0.003	0.004***	0.002	0.010***
	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.003)
High rainfall	-0.010***	0.007***	-0.018***	-0.009***	0.008***	-0.017***
	(0.003)	(0.002)	(0.004)	(0.003)	(0.002)	(0.004)
× Shannon	0.00001	-0.00007	0.006*	0.0006	0.002	0.003
	(0.002)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)
Shannon	0.021***	0.005	0.017***	0.016***	0.0002	0.010**
	(0.005)	(0.004)	(0.006)	(0.003)	(0.003)	(0.004)
Observations	24,371	19,158	11,087	24,371	19,158	11,087
Counties	2,127	1,716	1,471	2,127	1,716	1,471
R^2	0.735	0.769	0.744	0.733	0.769	0.743
Within R^2	0.159	0.249	0.031	0.154	0.247	0.031

Notes: OLS regressions reported with the log of crop yields in bushels per acre as the dependent variable. GDH measure growing degree hour (in 10,000) and HDH are harmful degree hour (in 1,000). Low rainfall and High rainfall are indicator variables for the first and third terciles of the precipitation distribution, respectively. Diversity is measured with we use the exponential Shannon index (the effective number of crops). Independent variables are mean-centered. Landscape diversity includes vegetation types that are not cultivated. All specifications include county and year fixed effects. Standard errors are clustered at the county level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

diversity as opposed to landscape diversity. A unit increase in the crop-based Shannon index raises corn yields by 2.1% and winter wheat yields by 1.7%, whereas the corresponding landscape coefficients fall to 1.6% and 1.0%, whereas estimates for soybean remain statistically insignificant. Consistent with Nelson and Burchfield (2021), this suggests that yield gains are concentrated in the cropped portion of the landscape, although our panel fixed effect estimation implies a more modest incremental contribution of non-crop area.

Estimates for interaction terms further confirm that crop diversity is the primary channel for resilience effects. For corn and soybeans, coefficients decline from 0.012 to 0.005 and from 0.012 to 0.007, respectively, when we broaden the index to the landscape. Resilience effects for low rainfall events also decline. Nonetheless, all coefficients are positive. In contrast, for

winter wheat, we observe a positive and statistically significant coefficient for the interaction between low rainfall and landscape diversity, while no such effect is found for crop diversity. This suggests that, at the average, landscape diversity contributes to enhancing yield benefits during years with low precipitation (see Tamburini et al., 2020). Across all three crops, GDH and high rainfall effects remain small and of the same sign in both specifications. Taken together, the results imply that evenness within the cropped area delivers the dominant share of yield and resilience benefits, while additional heterogeneity from non-crop vegetation provides smaller, crop-specific gains.

3.5 Results for robustness checks

We now report results for two robustness checks. First, we replace the contemporaneous Shannon index D_{it} with (i) its one-year lag (D_{it-1}) and (ii) a time-invariant value measured at the beginning of the sample period. Second, we augment the baseline specification with quadratic time trends: (i) a single trend common to all counties, (ii) state-specific trends, and (iii) county-specific trends. These trends control for changes in crop diversity and other unobserved factors affecting yields over time.

3.5.1 Robustness: lagged and pre-determined diversity

Table 6 presents the results using the one-year lag of the Shannon index ($D_{i,t-1}$) and a value of the index that is econometrically pre-determined in the time series sense, namely 2008 for corn and soybean and 2009 for winter wheat (denoted $D_{i,2008}$ and $D_{i,2009}$, respectively).[13] We follow the same structure as for Table 2, and include county and year fixed effects in all specifications. Standard errors clustered at the county-level are reported in parentheses.

Overall, the interaction terms that capture resilience to extreme weather shocks are largely unaffected by the timing assumptions. For all three crops, the interaction with HDH remains positive and highly statistically significant, and its magnitude approximately doubles when crop diversity is held fixed. This indicates that resilience to temperature shocks is not driven by contemporaneous crop-mix changes. Positive offsets to low rainfall years also persist, although

[13] For winter wheat the growing season spans two calendar years, with the first yield data observed in 2009. Results are similar if we use the Shannon index computed for 2008.

Table 6: Yields effects with lagged and predetermined crop diversity indices

	Corn		Soybean		Winter wheat	
	$D_{i,t-1}$	$D_{i,2008}$	$D_{i,t-1}$	$D_{i,2008}$	$D_{i,t-1}$	$D_{i,2009}$
	(1)	(2)	(3)	(4)	(5)	(6)
GDH	0.026***	0.022**	0.018*	0.014	-0.067***	-0.058***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)
× Shannon	-0.001	-0.028***	-0.009***	-0.018***	-0.012***	-0.017***
	(0.004)	(0.004)	(0.003)	(0.005)	(0.003)	(0.003)
HDH	-0.144***	-0.151***	-0.197***	-0.205***	-0.109***	-0.128***
	(0.005)	(0.006)	(0.006)	(0.006)	(0.015)	(0.014)
× Shannon	0.012***	0.026***	0.012***	0.023***	0.007	0.012*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.007)	(0.007)
Low rainfall	-0.029***	-0.032***	-0.040***	-0.041***	0.004	0.009*
	(0.003)	(0.003)	(0.003)	(0.003)	(0.005)	(0.005)
× Shannon	0.007***	0.003	0.004**	0.006***	0.003	0.006*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
High rainfall	-0.013***	-0.010***	0.007***	0.007***	-0.022***	-0.018***
	(0.003)	(0.003)	(0.002)	(0.002)	(0.004)	(0.004)
× Shannon	-0.0003	0.001	-0.0006	-0.0001	0.011***	0.008***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)
Shannon	0.012***		-0.012***		-0.009	
	(0.004)		(0.004)		(0.005)	
Observations	22,796	24,371	17,965	19,158	10,160	11,087
Counties	2,107	2,127	1,707	1,716	1,442	1,471
R^2	0.732	0.736	0.774	0.771	0.744	0.744
Within R^2	0.157	0.162	0.254	0.255	0.032	0.032

Notes: OLS regressions reported with the log of crop yields in bushels per acre as the dependent variable. GDH measure growing degree hour (in 10,000) and HDH are harmful degree hour (in 1,000). Low rainfall and High rainfall are indicator variables for the first and third terciles of the precipitation distribution, respectively. Diversity is measured with we use the exponential Shannon index (the effective number of crops). Independent variables are mean-centered. The table compares results when using Shannon lagged (D_{t-1}) vs. Shannon predetermined (D_{2008} or D_{2009}) as the diversity specification. All specifications include county and year fixed effects. Standard errors are clustered at the county level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

they become imprecise for corn in the fixed specification. For winter wheat, we observe a strong resilience effect in unusually wet years. Quantitatively, the offsetting effect corresponds to 50% (p<0.01) and 44% (p<0.01) for lagged and pre-determined specification, respectively.

We also note that the main diversity coefficient estimated in the lagged regression remains positive for corn, but turns negative for soybean and becomes statistically insignificant for winter wheat. This suggests that the coefficient ϕ^c should be interpreted as descriptive rather than causal.

Table 7: Yields effects with quadratic time trends

	Corn			Soybean			Winter wheat		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
GDH	0.020**	0.021**	0.024**	0.006	0.014	0.016*	-0.057***	-0.070***	-0.074***
	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.011)
× Shannon	0.009**	0.007*	0.007	-0.002	-0.001	-0.004	-0.010***	-0.009***	-0.009***
	(0.004)	(0.004)	(0.005)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
HDH	-0.143***	-0.141***	-0.146***	-0.196***	-0.194***	-0.195***	-0.123***	-0.118***	-0.119***
	(0.005)	(0.005)	(0.006)	(0.006)	(0.006)	(0.007)	(0.014)	(0.014)	(0.015)
× Shannon	0.012***	0.012***	0.013***	0.012***	0.013***	0.014***	0.002	0.005	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.008)	(0.008)	(0.009)
Low rainfall	-0.032***	-0.036***	-0.039***	-0.041***	-0.043***	-0.043***	0.008*	0.007	0.006
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.004)	(0.004)	(0.005)
× Shannon	0.005**	0.006***	0.007***	0.004*	0.004**	0.003	0.003	0.003	0.006*
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
High rainfall	-0.010***	-0.008***	-0.010***	0.007***	0.009***	0.009***	-0.018***	-0.016***	-0.019***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.003)	(0.004)	(0.004)	(0.004)
× Shannon	0.00001	-0.001	-0.0003	-0.0001	0.0002	-0.0004	0.006*	0.007**	0.009***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.004)
Shannon	0.021***	0.020***	0.023***	0.005	0.008**	0.009**	0.017***	0.018***	0.021***
	(0.005)	(0.005)	(0.006)	(0.004)	(0.004)	(0.004)	(0.006)	(0.006)	(0.007)
Observations	24,371	24,371	24,371	19,158	19,158	19,158	11,087	11,087	11,087
Counties	1,334	1,334	1,334	1,627	1,627	1,627	1,024	1,024	1,024
R^2	0.735	0.739	0.762	0.769	0.776	0.800	0.744	0.749	0.787
Within R^2	0.159	0.156	0.171	0.249	0.247	0.260	0.031	0.033	0.039
Time Trend	Common	State	County	Common	State	County	Common	State	County

Notes: OLS regressions reported with the log of crop yields in bushels per acre as the dependent variable. GDH measure growing degree hour (in 10,000) and HDH are harmful degree hour (in 1,000). Low rainfall and High rainfall are indicator variables for the first and third terciles of the precipitation distribution, respectively. Diversity is measured with we use the exponential Shannon index (the effective number of crops). Independent variables are mean-centered. Columns 1, 4, and 7 include a single trend for all counties; columns 2, 5, and 8 include state-specific trends and columns 3, 6 and 9 include county-specific trends. All specifications include county and year fixed effects. Standard errors are clustered at the county level and reported in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

3.5.2 Robustness: time trends

Table 7 reports results with quadratic time trends: a single trend for all counties (columns 1, 4, and 7), state-specific trends (columns 2, 5, and 8) and county-specific trends (columns 3, 6 and 9). The content of the table follows that of Table 2, and we include county and year fixed effects in all specifications. Standard errors clustered at the county-level are reported in parentheses.

The results with time trends confirm previous conclusion. Resilience effects estimated from interaction terms are consistent, although statistical inference can differ sightly. In particular, these results confirm a strong resilience effect for corn and soybean associated of HDH damages, and confirms that diversity attenuates winter wheat losses in unusually wet years. This lends support to the underlying identifying assumption and suggests that our findings are not driven by omitted, gradually evolving trends in yield growth.

4 Discussion and conclusion

In this paper, we have combined county-level yield data, high frequency weather observation, and high resolution cropland data to quantify how crop diversity mediates U.S. yield responses to weather shocks over 2008-2023. We measure crop diversity with the exponential Shannon index and estimate two-way fixed-effect regressions in which temperature and precipitation shocks are treated as plausibly exogenous. The interaction between weather variables and the diversity index identifies a resilience channel, showing that a more even crop portfolio reduces the marginal damage from extreme heat and moisture deficit.

Our results show that crop diversity matters both on average and in extreme weather. In line with Nelson and Burchfield (2021) and Burchfield et al. (2019), the Shannon index is positively and statistically significantly associated with corn and winter wheat yields, indicating that even outside extreme weather events diversity supports agricultural productivity. However, robustness checks with lagged diversity suggest that this main association may not be causal. More importantly, we report robust evidence that crop diversity mitigates yield losses from HDH exposure for corn and soybean. A resilience effect is also estimated for winter wheat in high rainfall years.

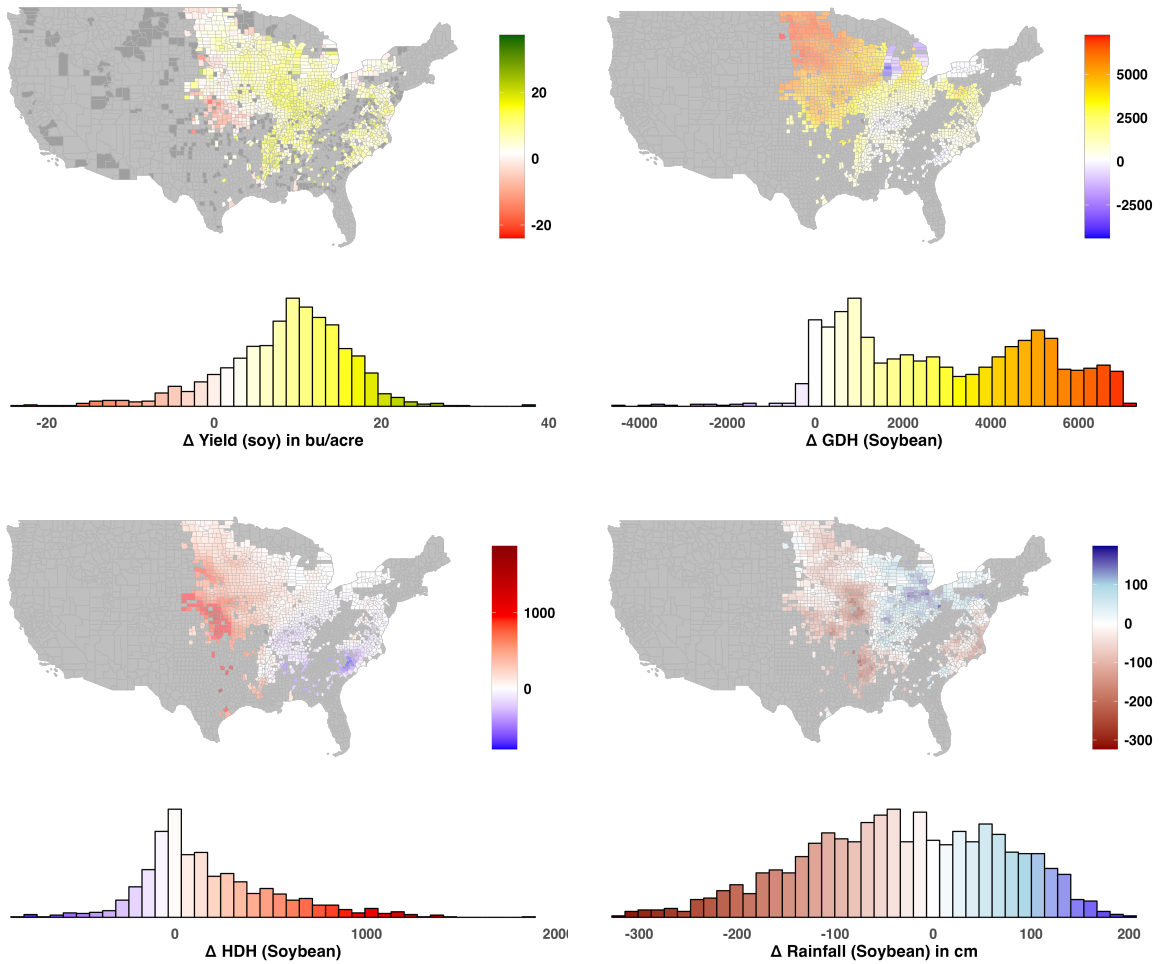
This evidence suggests that crop diversification can be part of climate adaptation policy, especially in regions that cannot rely indefinitely on irrigation. In particular, while irrigation can buffer crop production against weather shocks, it increasingly relies on unsustainable groundwater use. Scanlon et al. (2012) estimate that 60% of U.S. irrigation depends on groundwater. In the High Plains, 30% of the aquifer has already been depleted (Steward et al., 2013). Nationally, the share of groundwater in total withdrawals rose from 25% to nearly 30% between 2010 and 2015, with over half used for irrigation (Graham et al., 2021). Crop diversification therefore offers a complementary strategy for managing climate risk. Policy instruments such as crop-insurance premium discounts for diversified rotations, conservation payments that encourage minor crops, and technical assistance for non-traditional crops could facilitate an increase of crop diversity.

Our analysis is also subject to a number of limitations and caveats that could guide future research. First, our measure of diversity does not account for temporal practices such as multi-year rotations or fallowing. Integrating those practices could reveal additional resilience

mechanisms. Second, although the interaction coefficients appear causal, the level association between diversity and yields may still be confounded by unobserved management choices. Designs that exploit exogenous land-use shocks could clarify the direct benefit of crop diversity on yields, and would contribute to a better understanding of how diversity can be harnessed to promote agricultural productivity at the macro level.

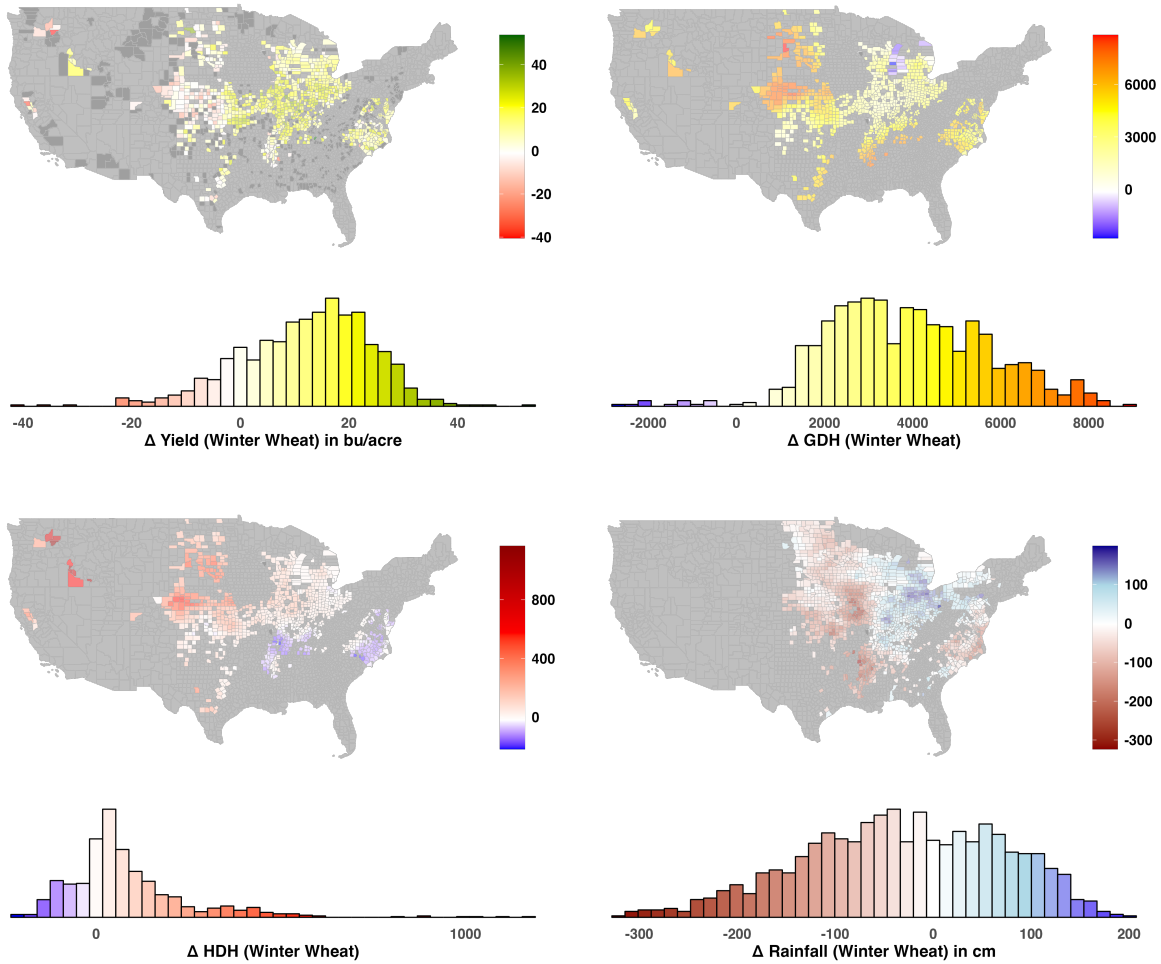
Appendix A Figures

Figure A1: County-level changes in soybean yield, growing and harmful degree hours, and growing-season rainfall, 2008-2023



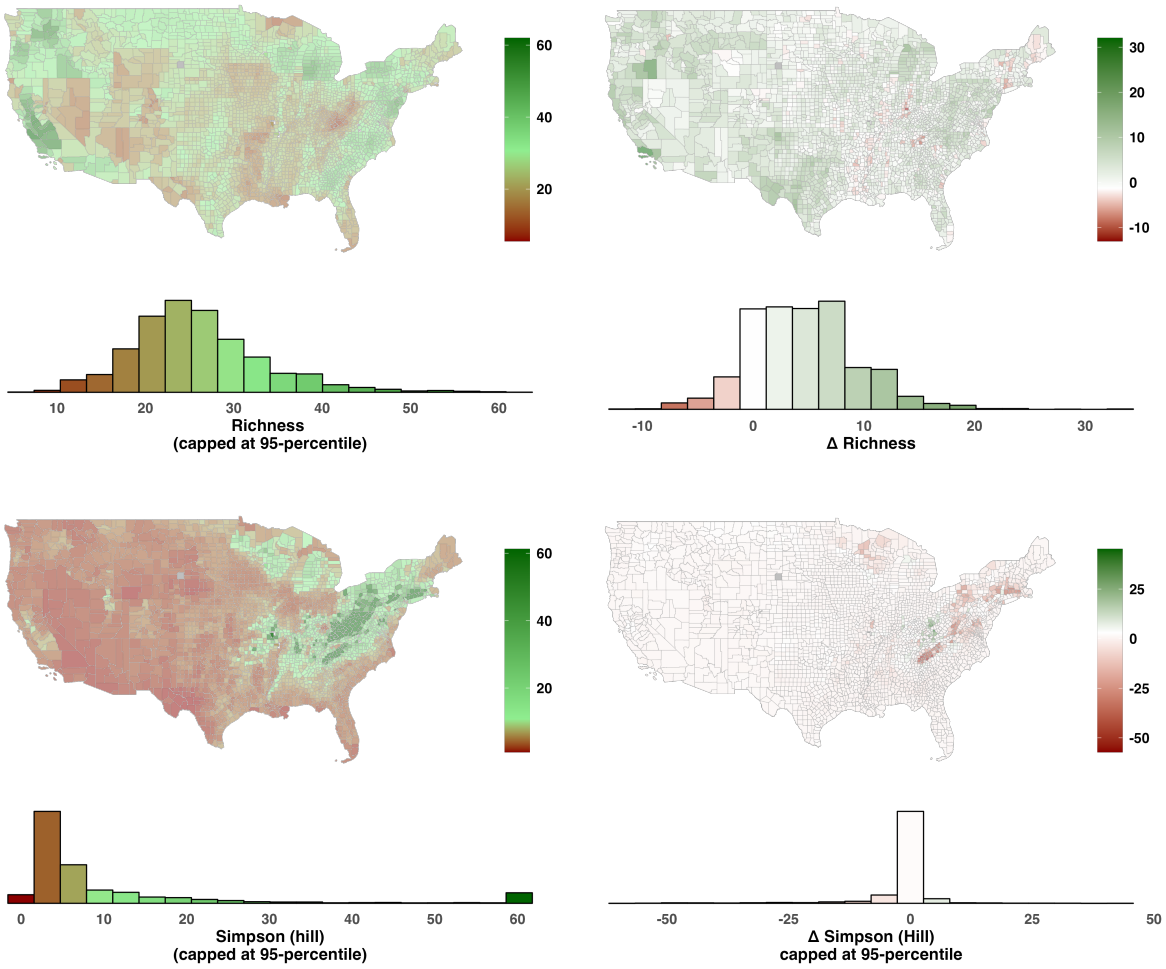
Notes: This figure reports differences in soybean yield and weather variables between 2008-2010 and 2021-2023 three year averages for all counties with non-suppressed observations in at least one year of each window. Histograms below the maps give the distribution of county changes. Upper left panel shows difference in corn yield in bu/acre. The upper right panel displays difference in growing degree hours (in 10,000°C-hours) and the lower left panel shows difference in harmful degree hours (in 1,000°C-hours). The lower right panel presents the difference in cumulative growing-season rainfall (cm).

Figure A2: County-level changes in winter wheat yield, growing and harmful degree hours, and growing-season rainfall, 2008 2023



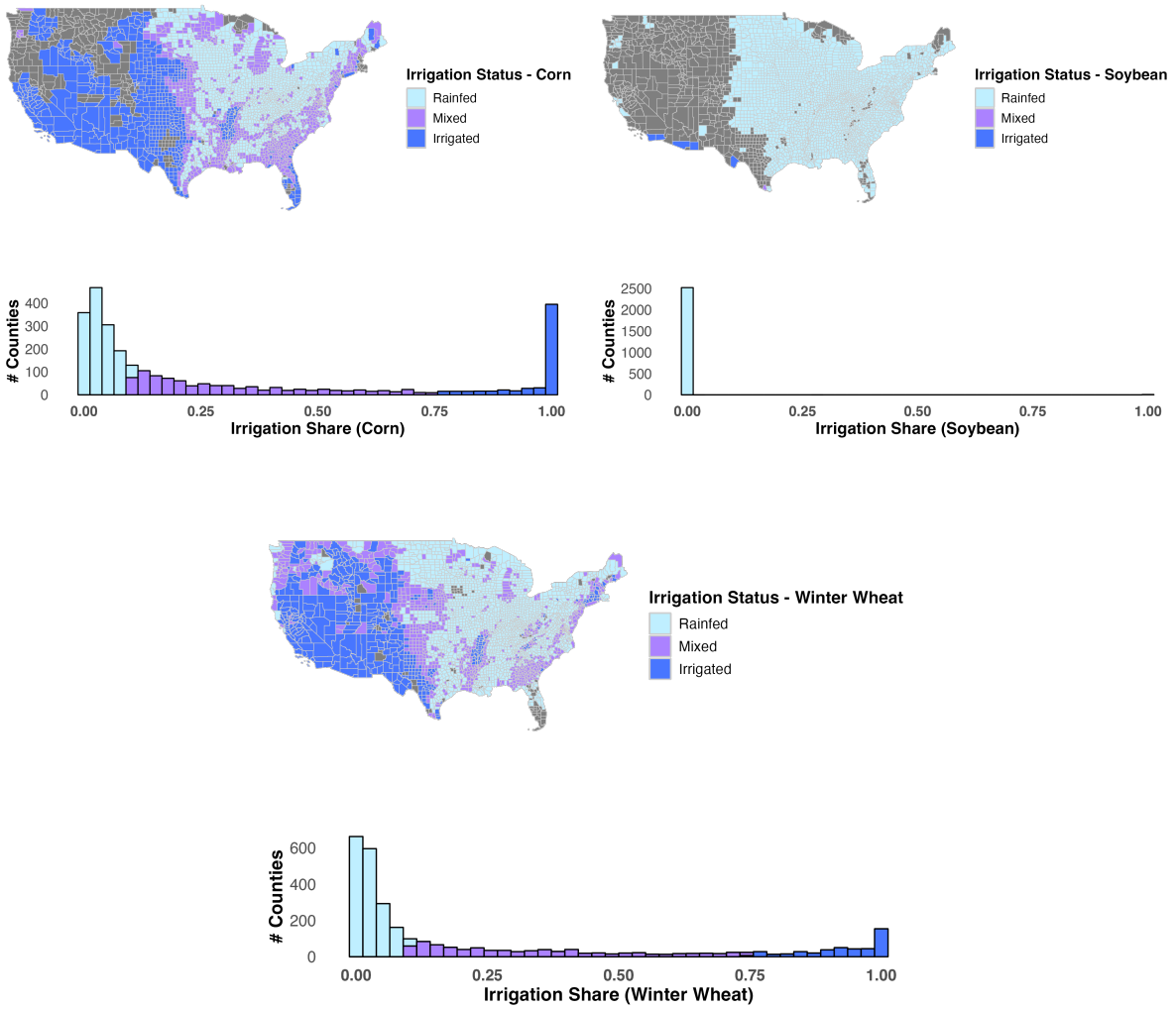
Notes: This figure reports differences in winter wheat yield and weather variables between 2008-2010 and 2021-2023 three year averages for all counties with non-suppressed observations in at least one year of each window. Histograms below the maps give the distribution of county changes. Upper left panel shows difference in corn yield in bu/acre. The upper right panel displays difference in growing degree hours (in 10,000°C-hours) and the lower left panel shows difference in harmful degree hours (in 1,000°C-hours). The lower right panel presents the difference in cumulative growing-season rainfall (cm).

Figure A3: Spatial distribution of richness and Simpson crop diversity



Notes: This figure reports the geographical distribution of the richness and Simpson crop diversity indices for the period 2008-2023. The two upper panels show the average value of the indexes for each county. The two bottom panels displays the change in each respective index between 2008-2010 and 2021-2023 three-year averages. Histograms below each map give the distribution of county averages and changes, respectively. To improve legibility Simpson values have been capped at their 95 percentile.

Figure A4: Irrigation status by crop



Notes: This figure reports irrigation status derived from the GAEZ+2015 dataset (Frolking et al., 2020), which reports irrigated and rainfed cropland area for 2015. For each county we compute the irrigation share and classify counties as rainfed (≤ 0.1), irrigated (≥ 0.75) and mixed in between (Schauberger et al., 2017). The accompanying histograms show the distribution of irrigation shares.

Appendix B Tables

Table B1: Omitted items in the cropland data layer

Clouds/No Data	Open Water
Developed	Perennial Ice/Snow
Nonag/Undefined	Developed/Open Space
Water	Developed/Low Intensity
Barren	Developed/Med Intensity
	Developed/High Intensity

Table B2: Cropland data layer categories considered non-cultivated

Other Hay/Non Alfalfa	Deciduous Forest
Sod/Grass Seed	Evergreen Forest
Switchgrass	Mixed Forest
Wetlands	Forest
Woody Wetlands	Grass/Pasture
Herbaceous Wetlands	Shrubland

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