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LETTER

Divergent changes in crop yield loss risk due to droughts over time in the US

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Abstract

Drought poses a major threat to agricultural production and food security. This study evaluates the changes in drought-induced crop yield loss risk for six crops (alfalfa, barley, corn, soybean, spring wheat, and winter wheat) between 1971–2000 and 1991–2020 across the contiguous US. Using a copula-based probabilistic framework, our results reveal a spatially heterogeneous change in yield risk to meteorological droughts, which varies with crop types. Regional analyses identify the largest temporal decline in yield risk in the Southeast and Upper Midwest, while the Northwest and South show an increase in risk. Among the considered anthropogenic and climatic drivers of crop productivity, changes in climatic variables such as high temperatures (e.g., killing degree days), vapor pressure deficit and precipitation show significantly stronger associations with changes in yield risk than irrigated area and nitrogen fertilizer application. Among the counties that observe drier drought events, only 55% exhibit an increase in crop yield loss risk due to drier droughts. The rest 45% show a decrease in yield loss risk due to mediation of favorable climatic and anthropogenic factors. Alarmingly, more than half (for barley and spring wheat), and one-third (for alfalfa, corn, soybean and winter wheat) of that the risk increasing regions have outsized influence on destabilizing national crop production. The findings provide valuable insights for policymakers, agricultural stakeholders, and decision-makers in terms of the potential ways and locations to be prioritized for enhancing local and national agricultural resilience and ensuring food security.

1. Introduction

Ensuring food security is a critical challenge in the 21st century, as the growing population and changing climate place unprecedented pressure on agricultural systems. Extreme climatic events pose a significant threat to global food security by disrupting agricultural production [1]. Among such events, drought stands out as a ubiquitous, recurring, and intensifying hazard with far-reaching impacts across various sectors including agriculture, economics, water resources and energy [2, 3]. Globally, around 38% of the land area is exposed to drought, with about 1.1 billion people residing in areas within the top 30th percentile of long-term average drought severity [4]. In the United States alone, drought events between 2000 and 2023 have incurred losses exceeding \$200 billion [5]. Alarmingly, drought is a multidimensional hazard that can manifest as precipitation shortages (meteorological drought), low soil moisture (agricultural drought), or depleted surface and groundwater water resources (hydrological drought) or low water availability and growing human water consumption (anthropogenic drought) [6, 7]. Agricultural sectors rely heavily on surface and sub-surface water resources and are highly vulnerable to drought stress [8, 9], often resulting in significant crop damage worldwide [10, 11].

Water stress due to drought—both severity and duration, hinders all phases of crop growth, from seed germination to shoot and root development and maturation [12]. Crop yield loss due to water stress often exceeds loss from all other stressors combined [13]. Evaluating drought impact on crop yield is essential to understand the extreme weather risks and develop mitigation strategies to ensure food security. Previous studies have extensively employed process-based [14–18] and statistical models [19–25], and empirical analysis over historical records [26], to study the effects of extreme climate events on crop yield. Machine learning and hybrid algorithms are also being increasingly used for analyzing climate-crop yield relationships [27–30]. Irrespective of the method used, prior studies have demonstrated that the impact of drought on crop yield, often quantified as crop yield sensitivity or loss risk, varies substantially across space and time due to differences in climate, management practices, and local and regional policies. For example, Zipper *et al* [20] employed statistical models to assess changes in drought impact on corn and soybean yields. Lobell *et al* [31] used statistical models to reveal an increasing corn yield sensitivity with vapor pressure deficit (VPD). A few assessments [21, 32, 33] quantified decadal or regional crop yield losses and dynamics. While these studies provide strong evidence of spatiotemporal differences, the drivers for changing drought sensitivity remain elusive. Understanding the key influential drivers for crop yield losses is crucial for enhancing drought resilience. Kamali *et al* [34] examined the spatial patterns of crop yield loss risk and contribution of climatic and soil parameters for sub-Saharan Africa. However, their analysis did not cover the role of potential influencers on temporal changes in drought risk. This study addresses the following five key questions: (a) to what extent have crop yield risks from droughts during the growing seasons historically changed in the US? (b) Are there distinct changes in the influencing factors on crop yields between regions that experience higher versus lower shifts in risk? (c) Does increased dryness of meteorological droughts during crop-growing seasons necessarily lead to a higher risk of reduced crop yields? (d) What are the relative contributions of changes in climatological and anthropogenic factors to these shifts in risk? and (e) What fraction of risk-increasing agricultural regions have a destabilizing effect on nation crop production?

This study aims to assess crop yield loss risk from drought for major crops across the continental United States and characterize the contrasts in potential drivers across regions exposed to increase vs. decrease in risks. We focus on six crops: alfalfa, barley, corn, soybean, spring wheat, and winter wheat, which are the major cereal crops in the US. Shifts in yield loss risk are evaluated using copula-based models between two overlapping 30-year periods, 1971–2000 and 1991–2020. We also examine how many counties across all considered crops have experienced increasingly drier droughts, and whether that necessarily indicates a heightened risk of crop yield loss. The study specifically highlights the risk trajectories within the major agricultural regions that are crucial for national production variability.

2. Methodology

2.1. Datasets

The county level crop yield, production, and harvested area records from 1971–2020 were obtained from the United States Department of Agriculture National Agricultural Statistics Service [35]. The planting and harvesting dates were retrieved from Sacks *et al* [36]. Daily temperature, precipitation and relative humidity time series at 0.25° spatial resolution were downloaded (for 1971–2020 period) from the GSWP3-W5 $\times$ 10^5 product of the Inter Sectoral Impact Model Intercomparison Project, which is a bias-corrected reanalysis product derived from both observations and models incorporating the WATCH forcing climate records [37–39]. Irrigated area was obtained from the global area equipped for irrigation dataset at 5 arcmin spatial resolution from 1971–2015 [40]. Gridded nitrogen fertilizer application rate for 1971–2015 was obtained at 5 $\times$ 5 km resolution from Cao *et al* [41] and combined with cropland area coverage data from Yu and Lu to obtain total nitrogen applied [42]. All gridded datasets were aggregated at the county scale.

2.2. Estimation of crop yield loss risk due to drought

County level SPI for each crop was calculated using a non-parametric approach by employing empirical Gringorten plotting position [43] method as:

$$p(x_r) = \frac{r - 0.44}{n + 0.12} \tag{1}$$

where x represents the precipitation, x_r is the growing season precipitation magnitude with rank r, $p(x_r)$ is the empirical probability of x_r, and n is the number of years under consideration. SPI was calculated by standardizing the empirical probability using the standard normal distribution [44].

$$\mathrm{SPI} = \Phi^{-1}(p(x_r)) \tag{2}$$

where Φ is the standard normal distribution.

Copula functions [45] were used to estimate the joint distribution of crop yield and SPI. Copulas enable representation of the joint distribution of two random variables with different marginal distributions. In other words, they are used to describe the dependence structure between random variables, allowing for modeling complex relationships in multivariate distributions. In the current context, copulas facilitate modeling of the relationship between crop yield and SPI. The joint distribution of crop yield (Y) and SPI can be given as follows:

$$F_{\mathrm{SPI},Y}(\mathrm{spi},y) = C\left[F_{\mathrm{SPI}}(\mathrm{spi}), F_Y(y)\right] \quad (3)$$

where $F_{\mathrm{SPI}}(\mathrm{spi})$ and $F_Y(y)$ are the marginal distributions of SPI and crop yield, respectively, and C is the copula function. Here we used seven commonly used copula families: Gaussian and Student t copulas from elliptical copula class; Clayton, Rotated Clayton, Gumbel–Hougaard, Rotated Gumbel and Frank copulas from Archimedean copula class, and Plackett copula (table S1). Copula parameters were obtained by maximum pseudo likelihood estimation and the best fit copula was selected based on the minimum Akaike information criteria (AIC) as implemented in the *R* package *VineCopula* [46]. An independent copula was selected if it had lower AIC than parametric copulas and no significant dependence between crop yield and SPI was detected. The goodness-of-fit of the copulas were then evaluated using the Cramér–von Mises statistic at 5% significance level for 500 bootstrap samples.

Crop yield loss risk (R_{YL}) was quantified based on the joint distribution of crop yield and SPI. R_{YL} is the conditional probability of lower than average (Y_{avg}) crop yield given drought condition specified by SPI $\leqslant -0.8$. The SPI threshold of -0.8 is generally considered for moderate drought by the US Drought Monitor [47].

$$R_{\mathrm{YL}} = P_{Y\langle Y_{\mathrm{avg}} |\, \mathrm{SPI} \leqslant -0.8} = \frac{P\left(Y < Y_{\mathrm{avg}},\ \mathrm{SPI} \leqslant -0.8\right)}{P\left(\mathrm{SPI} \leqslant -0.8\right)} \quad (4)$$

$$R_{\mathrm{YL}} = \frac{C\left(Y < Y_{\mathrm{avg}}, \mathrm{SPI} \leqslant -0.8\right)}{F_{\mathrm{SPI}}(-0.8)}. \quad (5)$$

Crop yield values were standardized to remove any trends due to technological developments in farming, improved seed varieties, and other agro-environmental factors. Following Troy *et al* [26], we implemented a 7 years moving window to detrend possible positive trends in crop yield records due to technological innovations.

2.3. Evaluation of changes in climatic and anthropogenic drivers vis-à-vis changes in crop yield loss risk and dryness of droughts

To assess the relative role of potential drivers for the changes in risk between 1971–2000 and 1991–2020, we investigated two major categories of contributors: anthropogenic and climatic. For anthropogenic controls, we examined county level irrigated area and nitrogen fertilizer application. The climate controls included precipitation (e.g. total precipitation and coefficient of variation of precipitation (PrecCV)) and temperature metrics (e.g. mean temperature (Tmean), growing degree days (GDD), killing degree days (KDD), and VPD. These variables were aggregated at county-level over the growing season based on their planting and harvesting dates. The considered factors are detailed in table S3. We analyzed the temporal shifts in potential contributors between the two time windows at each county level. We also examined their associations with increase or decrease in crop yield loss risk. Based on the growing period, which is different for crop types and across counties, the climate controls were aggregated considering the growing seasons for each county. It is important to note that the climate controls were aggregated only for the dry years (SPI < -0.8) as the risk assessment focuses specifically on such drought conditions.

We assessed changes in anthropogenic and climate controls between the recent (1991–2020) and the retrospective period (1971–2000), separately for counties where crop yield loss risk showed an increase ($\Delta R_{\mathrm{YL}} > 0$) and a decrease ($\Delta R_{\mathrm{YL}} < 0$). The wilcoxon rank sum test was performed to evaluate whether differences between potential controls were significant for risk-reducing versus risk-increasing counties. The association of a driver with risk reduction is considered positive if the increase in the driver is statistically significantly greater in risk-reducing counties, otherwise the association is considered negative. In other words, a positive association indicates the driver's contribution towards reducing yield risk. Assessment was also conducted on the changes in anthropogenic and climate factors for counties experiencing drier drought trends. This evaluation began by identifying, for each crop, the number of counties where net precipitation during growing season droughts decreased in the subsequent period. This process was repeated for all crops. Subsequently, the percentage of counties with drier droughts was calculated using the formula: 100 x (total number of counties experiencing drier droughts across all crops)/(total number of counties across all crops). A similar assessment was carried out for counties exhibiting wetter drought trends, resulting in the determination of the percentage of counties with wetter droughts.

2.4. Quantifying the relative influence of changes in various drivers on crop yield loss risk change

To assess the relative influence of changes in climatic and anthropogenic variables in determining whether a county has $\Delta R_{\mathrm{YL}} > 0$ or $\Delta R_{\mathrm{YL}} < 0$, we employed the SHAP (SHapley Additive exPlanations) analysis [48]. The SHAP assessment coupled with a random forest (RF) classification model, enables the quantification of each predictor variable's (i.e., changes in anthropogenic and climate controls) impact on the predictand (ΔR_{YL}). We utilized *TreeExplainer*, an explanation algorithm designed for tree-based machine learning models. This method computes explanations using exact shapley values and accounts for correlations among features [49]. This approach ensures that the feature importance analysis considers the correlations present between the different predictors.

2.5. Counties with potential to destabilize national crop production

R_{YL} was specifically evaluated for counties contributing to destabilization of national crop production. Following Mehrabi and Ramankutty [50], we identified the destabilizing counties for each crop based on counties contribution to national crop production variance. The destabilizing counties were the counties which have historically increased the inter-annual variance in national crop production. The contribution of each county in national crop production variance was calculated using the following instability index (I_Z):

$$I_z = \left(1 - \frac{\sigma^2_{n-z}}{\sigma^2}\right) * 100 \quad (6)$$

where σ^2 is the national variance, and σ^2_{n-z} is the national variance when county z is removed from the total number of producing counties. Stability index (I_Z) was calculated for each crop in each county. A positive I_Z (i.e. $\sigma^2 > \sigma^2_{n-z}$), represents destabilizing behavior of a county while negative values (i.e. $\sigma^2 < \sigma^2_{n-z}$) represent stabilizing behavior. Destabilizing counties increase the national variance with a positive index, while stabilizing counties decrease the national variance resulting in a negative index value.

3. Results

In majority of the counties, Clayton and Gumbel followed by Independent copulas were identified as the best-fitting copulas among the considered ones. These were followed by Gaussian and Frank copulas (figure S1). The goodness-of-fit statistic of the copulas were computed for both considered time periods, i.e. 1971–2000 and 1991–2020. In nearly all counties, the best performing copula showed a strong agreement with data (figure S2). Counties with poor copula fit ($p < 0.05$) or with insufficient data length (less than 25 years data) are discarded. Next, we analyzed the spatial and temporal changes in R_{YL} for 1971–2000 and 1991–2020.

3.1. Spatiotemporal assessments of R_{YL}

The crop yield loss risk (R_{YL}) for the six crops showed distinct spatial patterns (figure S3). Corn and to some extent soybean exhibited high risk in Southeastern states compared to Midwestern states. Winter wheat and alfalfa showed elevated risk in Great Plains, while spring wheat and barley showed greater risk in northern Montana. During 1971–2000, over one-third of the harvested area for alfalfa, barley, soybeans, winter wheat and spring wheat lies in the $R_{\mathrm{YL}} \geqslant 0.75$ zone, hereafter also referred as high-risk areas. This high-risk area tends to reduce in the recent era (1991–2020) for alfalfa, soybean and spring wheat, while increasing for barley, corn and winter wheat (figure S4(a)). Those counties that experienced R_{YL} in both periods were analyzed to assess changes in R_{YL} for the time slice 1991–2020 versus 1971–2000 to (ΔR_{YL}). Corn has the highest area (11.9 mil ha, 56% of its average area during 1971–2020) experiencing R_{YL} increase in 1991–2020 w.r.t. 1971–2000, followed by soybean (9.2 mil ha, 45%), winter wheat (7.9 mil ha, 62%), spring wheat (2 mil ha, 43%), alfalfa (1.3 mil ha, 45%) and barley (400 thousand ha, 30%) (table S2). For alfalfa, R_{YL} majorly decreases in Minnesota and Wisconsin, but increases in North Dakota, Arizona, New Mexico, Kansas and Colorado (figure 1). Corn and soybean exhibited similar $\boldsymbol{\Delta R_{\mathrm{YL}}}$ patterns, with elevated risk in southern states but reduced risk in southeastern and a few northern Corn Belt regions. Winter wheat exhibited higher risk in most of its production region except for the Southeast. For spring wheat, ΔR_{YL} decreased in North Dakota and Minnesota but increased in most of Montana. Barley showed reduced risk patterns in North Dakota, Idaho, and Montana. These results challenge the widespread notion that climate change will universally increase drought intensity and negatively impact crop production. Instead, the changes in risk exhibit divergent trends across different U.S. counties.

The aggregated change analysis for the risks in nine climatic regions defined by the National Centers for Environmental Information [51] showed the largest reduction in risk occurred in the Southeast followed by the Northern Rockies and Plains and Upper Midwest. In contrast, the Northwest had the greatest increase in risk followed by the South, West, Southwest, Ohio Valley and Northeast (figure 2). Specifically, an elevated corn yield loss risk is apparent across the Ohio Valley (Illinois, Indiana, Kentucky, Missouri, Ohio, Tennessee, West Virginia) and South (Arkansas, Kansas, Louisiana, Mississippi, Oklahoma, Texas). However, it shows a decline in the Southeast (Alabama, Florida, Georgia, North Carolina, South Carolina, Virginia), Upper Midwest (Iowa, Michigan, Minnesota, Wisconsin) and Northern Rockies and Plains (Montana, Nebraska, Dakotas, Wyoming). Similarly, soybean shows reduced risk in the majority of the regions, except for the South. This aligns with previous findings by Zipper *et al* [20]. Winter wheat exhibited decreased risk in the Southeast and Upper Midwest but increased risk in other regions. For spring wheat, risk declined in its major production areas of the Upper Midwest and Northern Rockies and Plain. Barley, primarily grown in Northern Rockies and Plain and Upper Midwest, showed reduced risk in these regions. Alfalfa displayed a

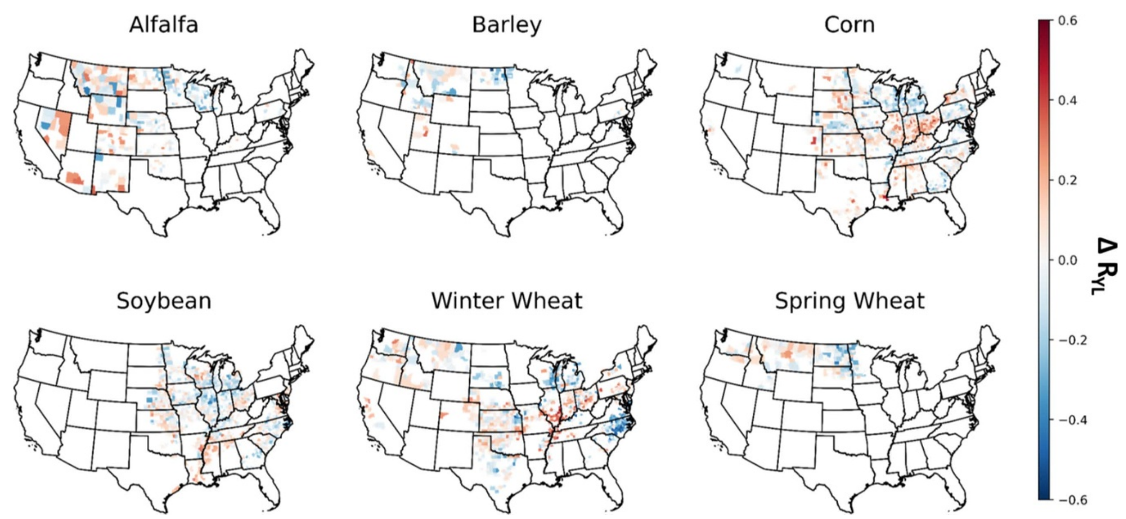

Figure 1. The difference in crop yield loss risk due to drought (ΔR_{YL}) between 1971–2000 and 1991–2020 for six crops across US counties. White region represents counties that reported fewer than 25 yield observation in either of the two time windows.

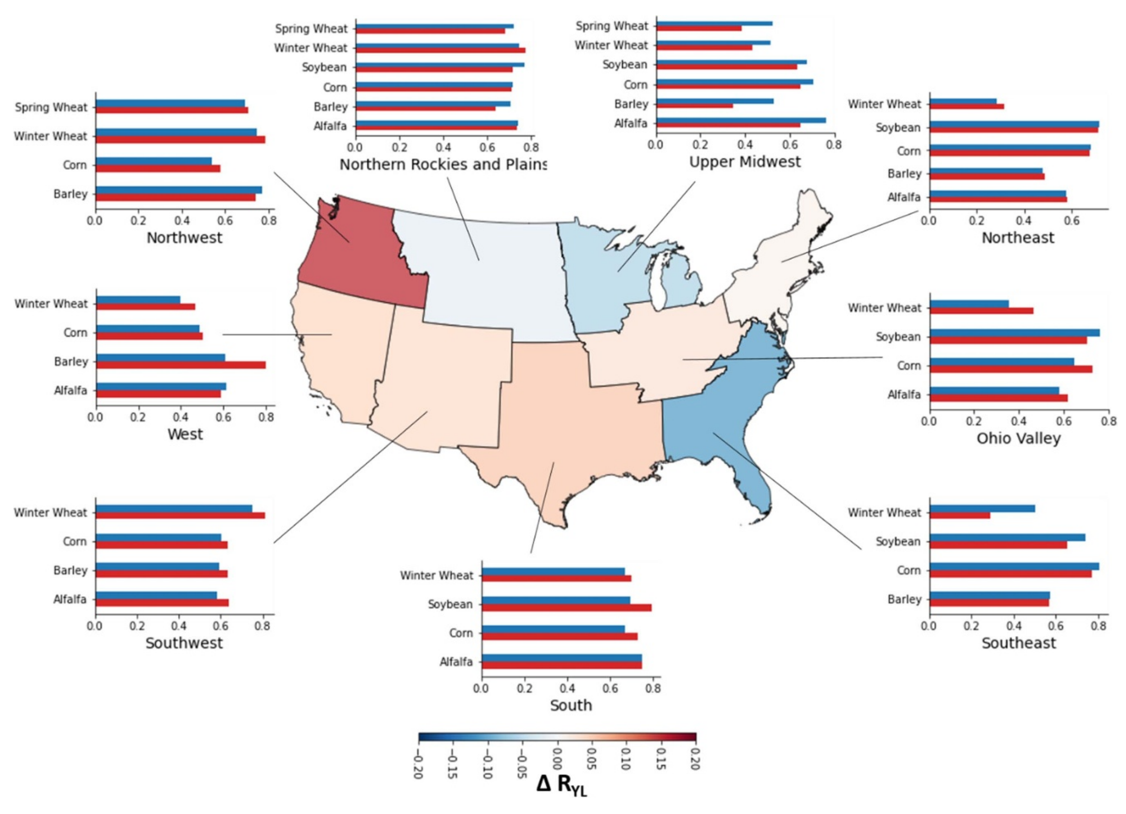

Figure 2. The difference in crop yield loss risk due to drought (ΔR_{YL}) in nine climatic regions. Bar plots depict the difference in crop yield loss risk for each crop within each region; blue and red bars represent the risk values in 1971–2000 and 1991–2020, respectively.

reduction in the risk in all the major producing regions except the Southwest. The national aggregated risk analysis showed crop yield loss risk significantly decreased for spring wheat, soybeans, barley and alfalfa (figure S5). Corn exhibits a minor increase in the national crop yield loss risk, whereas winter wheat shows a substantial increase in yield loss risk.

Separate risk evaluations were performed for rainfed versus irrigated corn and soybean yields across both study periods. Our analysis showed distinct risk profiles between the two practices. Rainfed yield displayed higher average risk, with mean R_{YL} of 0.78 (0.87) for corn and 0.79 (0.91) for soybeans in 1971–2000 (1991–2020). In contrast, irrigated yields showed a lower mean risk of 0.62 (0.56) for corn

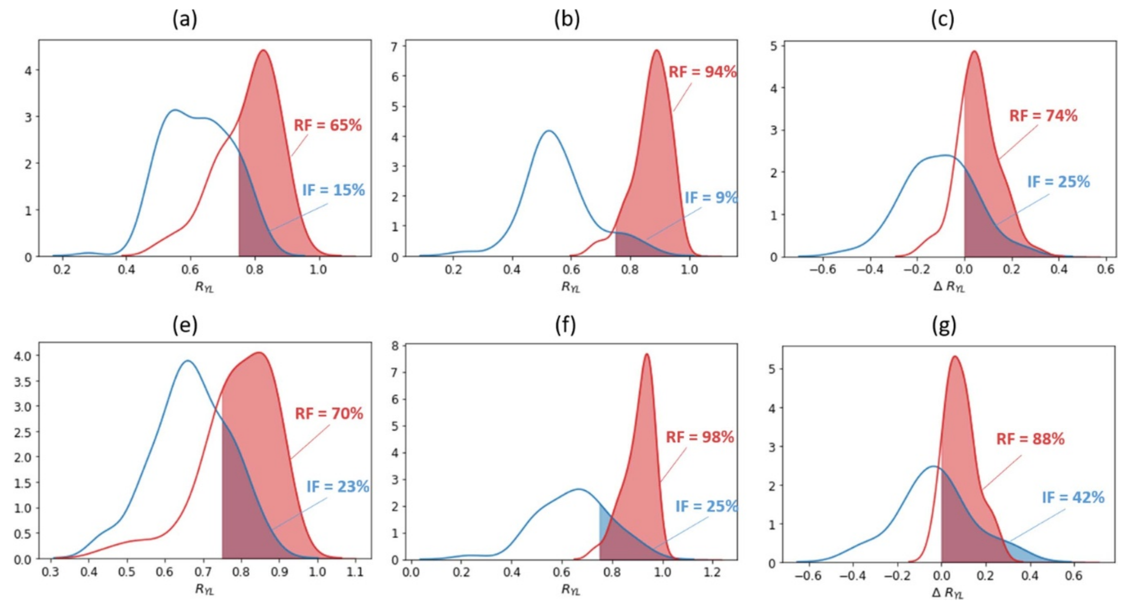

Figure 3. Density plots of rainfed (RF, in red), and irrigated (IF, in blue) crop yield loss risk (R_{YL}) for corn (top) and soybean (bottom). Subplots *a* and *e* depict the distribution of R_{YL} in 1971–2000, *b* and *f* in 1991–2020, and *c* and *g* illustrate the distribution of change in crop yield loss risk (ΔR_{YL}). The shaded area under the curves denotes fraction of counties where R_{YL} >0.75 in *a, b, e*, and *f*, and where ΔR_{YL} >0 in *c* and *g*.

and 0.67 (0.65) for soybeans (figure 3). The difference in the density distributions of risks in figure 3 demonstrates that crop yield losses due to water deficits are significantly less prevalent in irrigated regions compared to rain-fed crops. This highlights the role of water stress in shaping risk patterns and underscores the potential of irrigation expansion in mitigating drought risks to crop yields. Remarkably, only 15% (9%) of total irrigated corn counties had R_{YL} exceeding 0.75, while for rainfed counties R_{YL} exceeds 65% (94%) in 1971–2000 (1991–2020). Similarly, only 23% (25%) of irrigated soybean counties surpassed the 0.75 yield risk threshold, versus 70% (98%) of rainfed counties.

A larger proportion of irrigated areas displayed reduced risk (negative ΔR_{YL}) compared to rainfed counties for both crops. Specifically, 25% of irrigated corn counties experienced enhanced risk compared to 74% of the rainfed counties. Likewise, 42% of irrigated soybean counties had positive ΔR_{YL}, but the corresponding magnitude is around 88% for rainfed counties. These patterns indicate the rise in drought-related yield losses was more severe under rainfed conditions. Conversely, irrigated crops showed resilience, with a shift toward reduced yield loss risk over time. The comparative ΔR_{YL} results emphasize the protective role of irrigation against extreme drought impacts on crop yields during the analysis period.

3.2. Drivers of positive and negative ΔR_{YL}

We calculated the changes in anthropogenic and climatic drivers between the two time periods and evaluated their association with the risk reduction. The changes in seasonal precipitation from 1971–2000 to 1991–2020 were significantly different in risk-increasing (ΔR_{YL}>0) and risk-reducing (ΔR_{YL} <0) counties for alfalfa, corn and soybean. Moreover, precipitation increases were larger in risk reducing counties than risk increasing counties (figure 4) which indicates a positive association. This positive link between precipitation increase and risk reduction indicates that an increase in precipitation contributes toward lowering crop yield losses. Although mean precipitation changes were negative for barley, corn and winter wheat, risk increasing counties experienced more negative changes than risk reducing counties (figure S6). Apart from this, the PrecCV change was found statistically different for barley and corn and showed a negative association with risk reduction. For all crops, the mean increase in PrecCV was higher in risk-increasing counties, compared to risk-reducing counties. Risk-increasing counties also observed a higher increase in KDD compared to the risk-reducing counties. KDD reduced more in counties with risk reduction compared to those with risk-increases and the difference was found significant for all crops except winter wheat. This underscores the negative impact of increasing KDD on crop yield which has been noted in several studies [52–54]. Similarly, VPD showed a negative association with risk reduction with a significant higher increase in risk-increasing counties for all crops except alfalfa. The risk-increasing counties experienced more significant increase in mean temperature and GDD for corn and barley. Contrary to the previous findings, GDD showed a negative

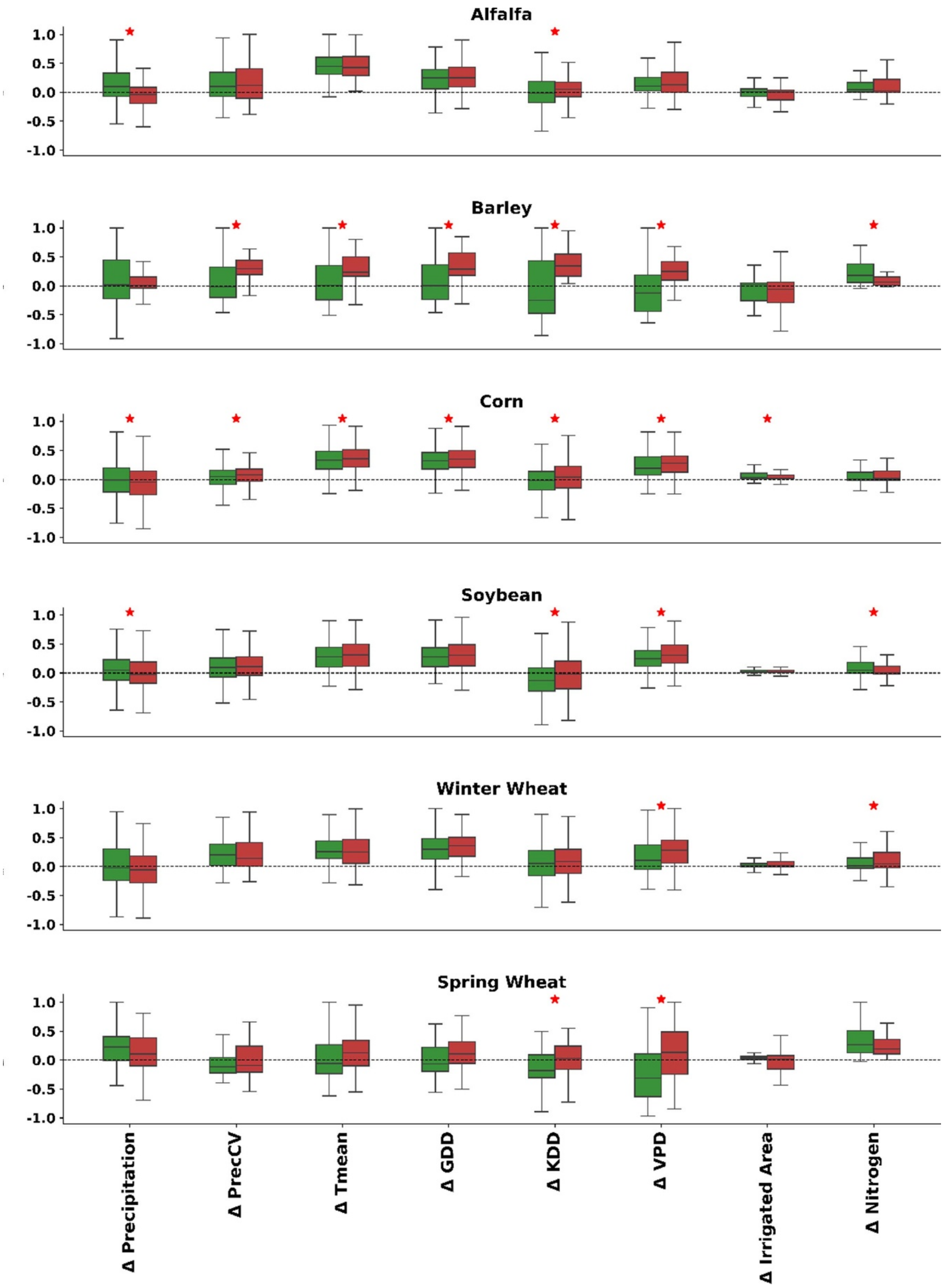

Figure 4. Box plots illustrating the change (Δ) in anthropogenic and climatic variables between 1971–2000 and 1991–2020 across counties. The green and red boxes represent change in the variables in risk-reducing and risk-increasing counties, respectively. The values on the *y*-axis are normalized to the range -1 to 1 by dividing the values by the absolute maximum value to preserve the sign. Box plot shows the median (solid line), interquartile range (i.e., from first quantile Q1 to third quantile Q3), and whiskers extending to Q1–1.5IQR and Q3 + 1.5IQR. An asterisk '*' above a box indicates a significant difference ($p < 0.05$) between risk-increasing and risk-reducing counties for a crop.

association with risk reduction for corn and barley. The possible reason for this can be the low feature importance of ΔGDD on ΔR_{YL} (figure 6) or the significant positive correlation between ΔGDD and ΔKDD with the impact of KDD being opposite to that of GDD (figure S7).

Positive association was also observed for irrigated area, however, it was significant only for

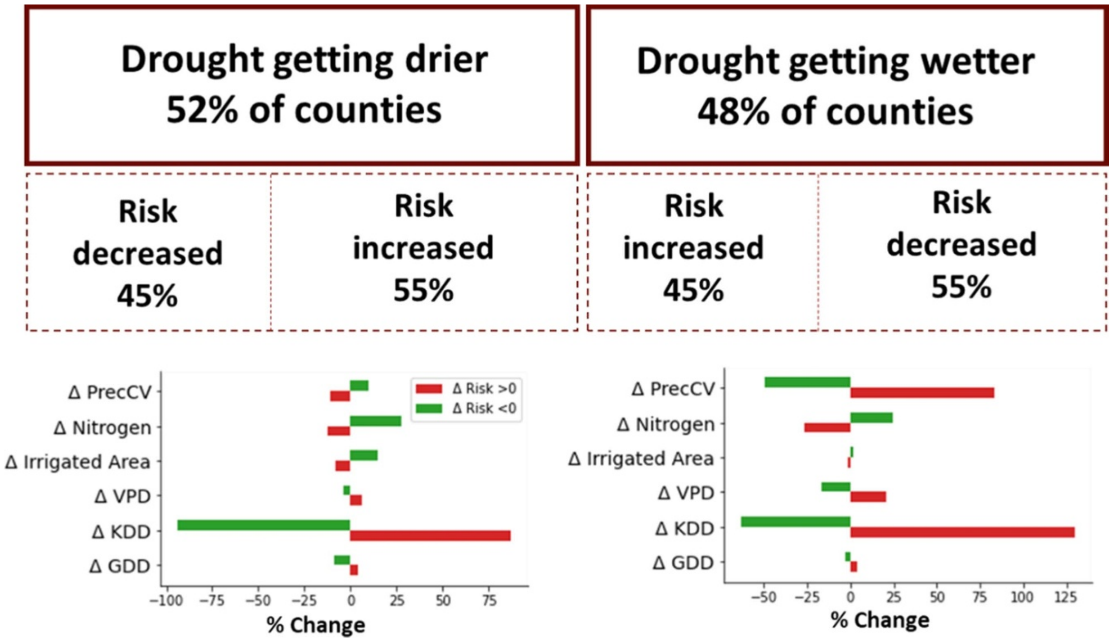

Figure 5. Percentage of counties across the considered crops where drought gets drier and wetter in the later time period, i.e. 1991–2020, w.r.t. 1971–2000. The bar charts show the changes in medians of climatic and anthropogenic variables across the two periods, for risk-increasing ($\Delta R_{YL} > 0$) and risk-reducing ($\Delta R_{YL} < 0$) counties, with respect to corresponding changes in these variables over all counties experiencing drier (left) and wetter (right) droughts.

corn. The mean irrigated area increased more in risk-reducing counties compared to risk-increasing counties for alfalfa, barley, corn and spring wheat. The mean irrigated area experienced a decrease in risk-increasing counties while an increase in risk-reducing counties for alfalfa and winter wheat. In contrast, irrigated area decreased for barley in both county types. The decrease is more pronounced in risk-increasing counties. The nitrogen application showed a significant difference for barley, winter wheat and soybean, where it exhibited a positive association for barley and soybean and a negative association for winter wheat.

3.3. Mediating roles of climatic and anthropogenic factors on crop yield loss risk change in counties experiencing drier drought shifts

Results showed around 52% of the counties, across the considered crops, observed drier droughts, i.e. precipitation during drought years reduced in the later time period. Notably, precipitation data for drought analysis were aggregated only for the crops' growing periods rather than on an annual basis as is usually performed in drought trend analysis studies [55–57]. Interestingly, despite the expectation that drier droughts would increase crop risk, only 55% of the counties experiencing drier droughts reported an increase in crop yield loss risk. Further analysis indicated the mediating roles of ancillary climatic and anthropogenic factors on drought-induced crop yield loss risk. For example, the median KDD change was −94% in the counties with reduced risk but drier droughts, compared to an 87% increase in the counties with increased crop yield loss risk and drier droughts (figure 5). These changes are relative to the median values across all counties affected by drier droughts. Additionally, in counties with reduced crop yield loss risks but drier droughts, the change in median irrigated area and nitrogen fertilizer application was 15% and 28% higher, respectively, compared to the overall medians of these variables in the drier drought counties. In contrast, in counties with increased crop yield loss risk and drier droughts, the changes in median irrigated area and nitrogen fertilizer application were 8% and 12% lower, respectively. Similarly, among the counties with wetter droughts (precipitation increased during the drought periods within the crop growing seasons), 45% of the counties reported an increase in the crop yield loss risk. These results can be explained by the unfavorable changes in climatic and anthropogenic factors. For example, the median KDD and PrecCV in wetter drought counties were found to be higher than their median values during the latter period, while irrigated area and nitrogen application were found to be lower in these risk increasing counties. Overall, these findings emphasize that the changes in drought severity alone do not fully account for the variations in crop yield loss risk. They also highlight the significant mediating effects of climatic and anthropogenic factors in influencing these risk changes.

3.4. Relative influence of the considered climatic and anthropogenic factors on ΔR_{YL}

The RF model performed satisfactorily with an accuracy of 0.62. Results showed that changes in VPD is

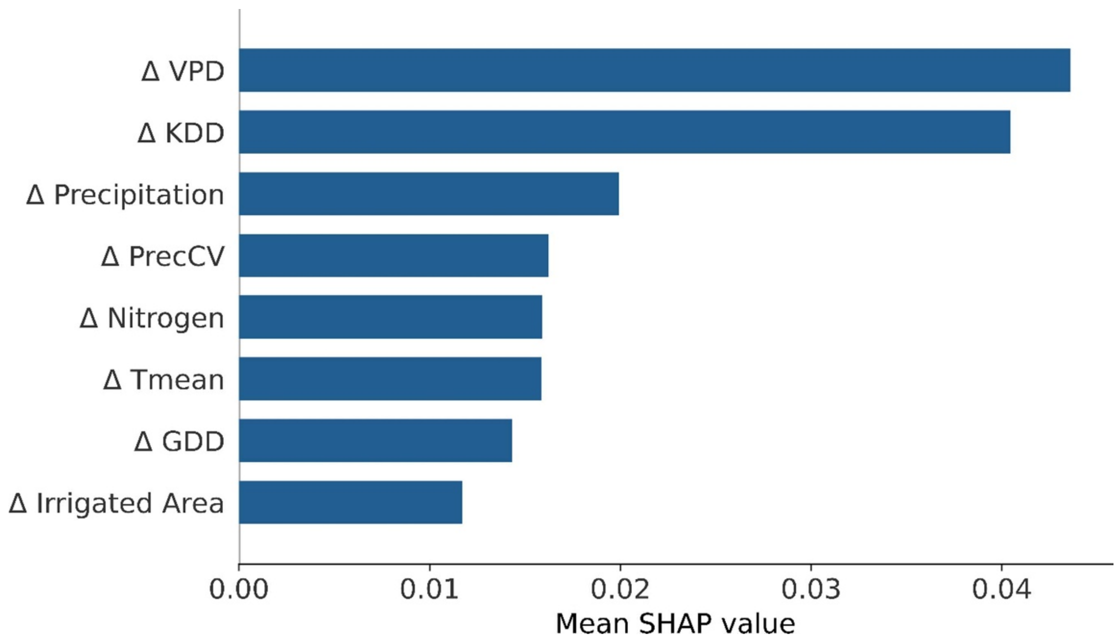

Figure 6. Relative importance of changes in climatic and anthropogenic variables calculated using the SHAP values. Higher SHAP values signify greater importance of a variable on model prediction.

the most influential variable, which is closely followed by changes in the KDD and precipitation (figure 6). Drivers such as difference in nitrogen application, mean temperature, and GDD exhibited relatively lower feature importance values. While previous studies have underscored the important role of VPD in drought impacts on crop yield [58, 59], our findings reveal that changes in VPD and KDD have a far greater influence than variations in nitrogen fertilization and irrigation area transitions within the analysis region and time period.

3.5. Change in crop yield loss risk in destabilizing agricultural regions

Following on the identification of 'hotspot' counties where crop yield loss due to drought have changed over the years and the key causal drivers for this change, next we assessed whether hotspots are occurring in regions that are known to have the potential to destabilize national crop production. To this end, we identified destabilizing counties for each crop using an instability index that measures individual county contributions to national production variance. Counties having a positive instability index value, deemed as major destabilizing regions, are selected for further analysis. These influential counties collectively contributed to the national average production, accounting for 52%, 70%, 67%, 66%, 63%, and 83% of the total average production from 1971 to 2020 for alfalfa, barley, corn, soybean, winter wheat, and spring wheat, respectively. Notably, individual counties can exert substantial local influence in the variance of national production, with maximum contributions reaching 1.5%, 5.4%, 1.3%, 1.2%, 2.1%, and 4.4% for alfalfa, barley, corn, soybean, winter wheat, and spring wheat, respectively (figure S8). We identified the destabilizing regions for each crop. The fraction of risk increasing counties that emerged as destabilizing regions for alfalfa, barley, corn, soybean, winter wheat, and spring wheat were 32%, 57%, 33%, 35%, 39%, and 71%, respectively. For alfalfa, the majority of such counties are situated in North Dakota and Wisconsin. Corn and soybeans display similar geographic patterns, with destabilizing and risk-increasing counties spatially clustered in Iowa, Illinois, Indiana, Ohio, Nebraska and Minnesota (figure 7). A few soybean-growing destabilizing counties in Mississippi and Tennessee also showed increased risk. Kansas, Oklahoma and Texas experienced the elevated risk with destabilizing effects for winter wheat. For spring wheat, counties in Montana and North Dakota showed such effect; and for barley, most of the counties considered for the ΔR_{YL} analysis which were situated in Montana and Idaho had destabilizing and risk increasing effects.

4. Discussion

The crop yield loss risk assessment to drought is vital for understanding the vulnerability of agricultural systems. This study investigates the historical spatiotemporal changes in crop yield loss risk due to meteorological drought across six major crops in the US. The findings reveal a heterogeneous impact of meteorological drought on crops, varying with crop types and growing regions. Utilizing crop yield and precipitation records from 1971 to 2020, along with copula-based probabilistic modeling, we demonstrate that among the six major crops analyzed, corn and winter wheat experienced an increase-in nationally

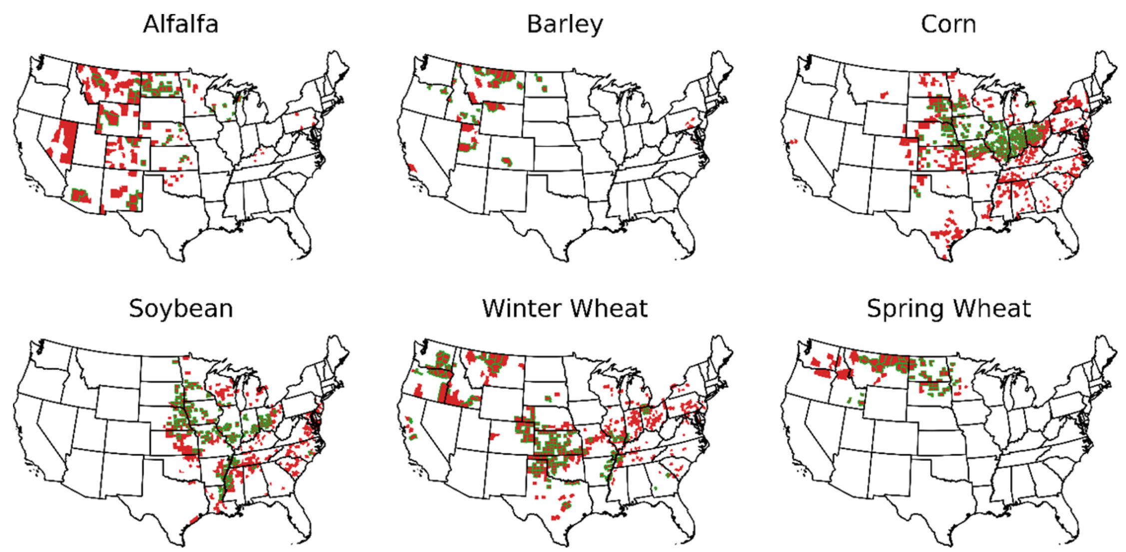

Figure 7. Spatial distribution of risk-increasing counties (shown in red) and destabilizing counties (i.e. $I_z > 0$, with green boundary) for the six selected crops.

aggregated crop yield loss risk, while alfalfa, barley, soybean, and spring-wheat saw a reduction. Given the divergent trends of crop yield loss risk, the results challenge the belief that climate change will intensify droughts and harm crop production. The crop yield loss risk change analysis over the nine homogeneous climatic regions of the US revealed that crops in the Southeast and Upper Midwest regions experienced the highest reduction, whereas the Northwest and South witnessed a higher increase in risk between 1971–2000 and 1991–2020. A comparative analysis of rainfed versus irrigated crop yield loss risk provides valuable insights into the potential of irrigation to mitigate drought stress impacts on crop production. Irrigated crops showed a lower likelihood of crop yield loss risk compared to its rainfed counterparts, with a similarly low increase in risk for irrigated crops.

Next, this study examined the potential anthropogenic and climate controls for changes in crop yield loss risk due to drought. Drivers such as changes in precipitation, KDD, VPD, GDD, irrigated area, and PrecCV significantly varied between regions experiencing risk increases or reductions over time. The higher precipitation or the increase in irrigated area in risk-reducing counties indicate a favorable impact on risk reduction. In contrast, counties with increased exposure to climate stressors, such as incidence of high-temperatures, as captured by KDD, or higher precipitation variability showed an increased risk of crop yield loss.

The results revealed that only 52% of the counties across all considered crops experienced drier droughts, defined as a reduction in precipitation during the growing season droughts between 1971–2000 and 1991–2020. Among these counties, a significant proportion (45%) showed a decrease in crop yield loss risk. This counterintuitive result is attributed to favorable changes in climatic and anthropogenic factors, such as an increase in irrigated areas, enhanced nitrogen application, and a reduction in KDD. These factors mitigated the expected negative impact of drier droughts on crop yields. Conversely, counties that experienced wetter droughts during the latter period were also found to exhibit increasing crop yield loss risk 45% of instances. This increase in risk was associated with a reduction in irrigated areas, decreased nitrogen application, and an increase in KDD. These findings challenge the general expectation that drier droughts invariably lead to higher crop yield loss risk, highlighting the complex interplay of climatic and anthropogenic factors in determining crop yield outcomes. Additional analyses revealed that the examined climate controls had higher contribution to crop yield loss risk than the two considered anthropogenic controls. Notably, more than half of barley and spring wheat and one-third of alfalfa, corn, soybean and winter wheat risk-increasing counties had a destabilizing effect on the national crop production. It is to be noted that the study identifies associations between changes in climatological and anthropogenic variables vis-à-vis yield risk change, but that does not establish causal relationships. It is possible that additional covarying latent factors could be causing the risk change. The study uses specific time windows to assess changes in yield risks, and it may not necessarily be representative of long-term trends and anomalies that occur outside these periods. The analysis will benefit from finer spatial resolution data of climatological and anthropogenic variables. Despite aforementioned limitations, by bridging the research gap between assessments of drought impact on crop yield losses for major crops, and the potential contributing drivers, this study provides critical insights into the impact of various anthropogenic and climate controls on the evolving risk of crop yield to drought. By identifying the crop types and regions where yield risks to droughts are being significantly altered, policymakers can prioritize resources and devise resilient adaptation practices to mitigate the adverse impacts. Focusing on measures to mitigate drought impacts on crops that have experienced an increase in yield loss risk could be made a priority. Policymakers can utilize the findings from this study to develop targeted policies aimed at reducing the vulnerability of cropping systems to drought. For example, policies could incentivize the adoption of drought-resistant crop varieties, promote sustainable irrigation practices, or provide financial support for fertilizers or extensions for soil testing in counties experiencing enhanced crop yield loss risk due to drought. This could involve crop diversification or adjusting planting schedules based on drought forecasts. Policies that incentivize sustainable agricultural practices, such as conservation tillage, cover cropping, and soil moisture management, could be used to improve resilience against droughts, especially in regions facing enhancement in yield risks. Overall, the findings can aid in enhancing agricultural resilience both locally and nationally, and ensure food security amidst changing climate conditions. Future work could incorporate crop modeling into the analysis to help understand the changing regime of crop yield loss risk vis-à-vis changes in different drought characteristics, and to develop alternative mitigation scenarios to ensure yield resilience. The methodology used in this study can be applied in future research to examine how other types of droughts, such as groundwater drought, hydrologic drought, or socioeconomic drought, influence changes in crop yield loss risks.

Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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References

[1] Wheeler T and von Braun J 2013 Climate change impacts on global food security *Science* **341** 508–13
[2] Wilhite D A 2016 *Droughts: A Global Assesment* (Routledge)
[3] Hayes M J, Svoboda M D, Wardlow B D, Anderson M C and Kogan F 2012 Drought monitoring: historical and current perspectives
[4] Dilley M, Chen R S, Deichmann U, Lerner-Lam A L and Arnold M 2005 *Natural Disaster Hotspots: A Global Risk Analysis* (World Bank)
[5] Information (NCEI) N C for E U.S. billion-dollar weather and climate disasters, 1980 present (NCEI Accession 0209268)
[6] Dai A 2011 Drought under global warming: a review *WIREs Clim. Change* **2** 45–65
[7] AghaKouchak A *et al* 2021 Anthropogenic drought: definition, challenges, and opportunities *Rev. Geophys.* **59** e2019RG000683
[8] Meza I *et al* 2020 Global-scale drought risk assessment for agricultural systems *Nat. Hazards Earth Syst. Sci.* **20** 695–712
[9] Rampino P, Pataleo S, Gerardi C, Mita G and Perrotta C 2006 Drought stress response in wheat: physiological and molecular analysis of resistant and sensitive genotypes *Plant Cell Environ.* **29** 2143–52
[10] Lesk C, Rowhani P and Ramankutty N 2016 Influence of extreme weather disasters on global crop production *Nature* **529** 84–87
[11] Lesk C, Coffel E, Winter J, Ray D, Zscheischler J, Seneviratne S I and Horton R 2021 Stronger temperature–moisture couplings exacerbate the impact of climate warming on global crop yields *Nat. Food* **2** 683–91
[12] Dietz K-J, Zörb C and Geilfus C-M 2021 Drought and crop yield *Plant Biol.* **23** 881–93
[13] Clough J M, Peet M M and Kramer P J,1981 Drought, stress, and the origin of adaptations *Plant Physiol.* 67 1007–10
[14] Lobell D B, Hammer G L, McLean G, Messina C, Roberts M J and Schlenker W 2013 The critical role of extreme heat for maize production in the United States *Nat. Clim. Change* **3** 497–501
[15] Moriondo M, Giannakopoulos C and Bindi M 2011 Climate change impact assessment: the role of climate extremes in crop yield simulation *Clim. Change* **104** 679–701
[16] Guo S *et al* 2022 Impacts of mean climate and extreme climate indices on soybean yield and yield components in Northeast China *Sci. Total Environ.* **838** 156284
[17] Chen X, Wang L, Niu Z, Zhang M, Li C and Li J 2020 The effects of projected climate change and extreme climate on maize and rice in the Yangtze River Basin, China *Agric. For. Meteorol.* **282–283** 107867
[18] Cammarano D and Tian D 2018 The effects of projected climate and climate extremes on a winter and summer crop in the southeast USA *Agric. For. Meteorol.* **248** 109–18
[19] Hlavinka P, Trnka M, Semerádová D, Dubrovský M, Žalud Z and Možný M 2009 Effect of drought on yield variability of key crops in Czech Republic *Agric. For. Meteorol.* **149** 431–42
[20] Zipper S C, Qiu J and Kucharik C J 2016 Drought effects on US maize and soybean production: spatiotemporal patterns and historical changes *Environ. Res. Lett.* **11** 094021
[21] Liu X, Pan Y, Zhu X, Yang T, Bai J and Sun Z 2018 Drought evolution and its impact on the crop yield in the North China Plain *J. Hydrol.* **564** 984–96
[22] Schlenker W and Roberts M J 2009 Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change *Proc. Natl Acad. Sci.* **106** 15594–8
[23] Ray D K, Gerber J S, MacDonald G K and West P C 2015 Climate variation explains a third of global crop yield variability *Nat. Commun.* **6** 5989
[24] Leng G 2021 Maize yield loss risk under droughts in observations and crop models in the United States *Environ. Res. Lett.* **16** 024016

[25] Madadgar S, AghaKouchak A, Farahmand A and Davis S J 2017 Probabilistic estimates of drought impacts on agricultural production *Geophys. Res. Lett.* **44** 7799–807
[26] Troy T J, Kipgen C and Pal I 2015 The impact of climate extremes and irrigation on US crop yields *Environ. Res. Lett.* **10** 054013
[27] Vogel E, Donat M G, Alexander L V, Meinshausen M, Ray D K, Karoly D, Meinshausen N and Frieler K 2019 The effects of climate extremes on global agricultural yields *Environ. Res. Lett.* **14** 054010
[28] Feng P, Wang B, Liu D L, Waters C and Yu Q 2019 Incorporating machine learning with biophysical model can improve the evaluation of climate extremes impacts on wheat yield in south-eastern Australia *Agric. For. Meteorol.* **275** 100–13
[29] Crane-Droesch A 2018 Machine learning methods for crop yield prediction and climate change impact assessment in agriculture *Environ. Res. Lett.* **13** 114003
[30] Sidhu B S, Mehrabi Z, Ramankutty N and Kandlikar M 2023 How can machine learning help in understanding the impact of climate change on crop yields? *Environ. Res. Lett.* **18** 024008
[31] Lobell D B, Roberts M J, Schlenker W, Braun N, Little B B, Rejesus R M and Hammer G L 2014 Greater sensitivity to drought accompanies maize yield increase in the U.S. Midwest *Science* **344** 516–9
[32] Wang Q *et al* 2014 Temporal-spatial characteristics of severe drought events and their impact on agriculture on a global scale *Quat. Int.* **349** 10–21
[33] Mokhtar A *et al* 2022 Assessment of the effects of spatiotemporal characteristics of drought on crop yields in southwest China *Int. J. Climatol.* **42** 3056–75
[34] Kamali B, Jahanbakhshi F, Dogaru D, Dietrich J, Nendel C and AghaKouchak A 2022 Probabilistic modeling of crop-yield loss risk under drought: a spatial showcase for sub-Saharan Africa *Environ. Res. Lett.* **17** 024028
[35] USDA-NASS Q USDA NASS QuickStats Ad-hoc query tool
[36] Sacks W J, Deryng D, Foley J A and Ramankutty N 2010 Crop planting dates: an analysis of global patterns *Glob. Ecol. Biogeogr.* **19** 607–20
[37] Kim H 2017 Global soil wetness project phase 3 atmospheric boundary conditions (experiment 1)
[38] Cucchi M, Weedon G P, Amici A, Bellouin N, Lange S, Müller Schmied H, Hersbach H and Buontempo C 2020 WFDE5: bias-adjusted ERA5 reanalysis data for impact studies *Earth Syst. Sci. Data* **12** 2097–120
[39] Lange S WFDE5 over land merged with ERA5 over the ocean (W5E5 v2.0)
[40] Mehta P, Siebert S, Kummu M, Deng Q, Ali T, Marston L, Xie W and Davis K 2022 Global area equipped for irrigation dataset 1900–2015
[41] Cao P, Lu C and Yu Z 2018 Historical nitrogen fertilizer use in agricultural ecosystems of the contiguous United States during 1850–2015: application rate, timing, and fertilizer types *Earth Syst. Sci. Data* **10** 969–84
[42] Yu Z and Lu C 2018 Historical cropland expansion and abandonment in the continental U.S. during 1850–2016 *Glob. Ecol. Biogeogr.* **27** 322–33
[43] Gringorten I I 1963 A plotting rule for extreme probability paper *J. Geophys. Res.* **68** 813–4
[44] Hao Z, AghaKouchak A, Nakhjiri N and Farahmand A 2014 Global integrated drought monitoring and prediction system *Sci. Data* **1** 140001
[45] Nelsen R B 2006 *An Introduction to Copulas* (Springer)
[46] Nagler T *et al* 2023 VineCopula: statistical inference of vine copulas
[47] Svoboda M *et al* 2002 The drought monitor *Bull. Am. Meteorol. Soc.* **83** 1181–90
[48] Lundberg S M and Lee S-I 2017 A unified approach to interpreting model predictions *Advances in Neural Information Processing Systems* vol 30 (Curran Associates, Inc.)
[49] Lundberg S M, Erion G, Chen H, DeGrave A, Prutkin J M, Nair B, Katz R, Himmelfarb J, Bansal N and Lee S-I 2020 From local explanations to global understanding with explainable AI for trees *Nat. Mach. Intell.* **2** 56–67
[50] Mehrabi Z and Ramankutty N 2019 Synchronized failure of global crop production *Nat. Ecol. Evol.* **3** 780–6
[51] Karl T and Koss W J 1984 Regional and national monthly, seasonal, and annual temperature weighted by area, 1895–1983
[52] Deryng D, Conway D, Ramankutty N, Price J and Warren R 2014 Global crop yield response to extreme heat stress under multiple climate change futures *Environ. Res. Lett.* **9** 034011
[53] Beillouin D, Schauberger B, Bastos A, Ciais P and Makowski D 2020 Impact of extreme weather conditions on European crop production in 2018 *Phil. Trans. R. Soc.* B **375** 20190510
[54] Burchfield E, Matthews-Pennanen N, Schoof J and Lant C 2020 Changing yields in the Central United States under climate and technological change *Clim. Change* **159** 329–46
[55] Andreadis K M and Lettenmaier D P 2006 Trends in 20th century drought over the continental United States *Geophys. Res. Lett.* **33** L10403
[56] Ganguli P and Ganguly A R 2016 Space-time trends in U.S. meteorological droughts *J. Hydrol.* **8** 235–59
[57] Sheffield J, Wood E F and Roderick M L 2012 Little change in global drought over the past 60 years *Nature* **491** 435–8
[58] Liao Q, Ding R, Du T, Kang S, Tong L and Li S 2022 Stomatal conductance drives variations of yield and water use of maize under water and nitrogen stress *Agric. Water Manage.* **268** 107651
[59] Kimm H, Guan K, Gentine P, Wu J, Bernacchi C J, Sulman B N, Griffis T J and Lin C 2020 Redefining droughts for the U.S. Corn Belt: the dominant role of atmospheric vapor pressure deficit over soil moisture in regulating stomatal behavior of Maize and Soybean *Agric. For. Meteorol.* **287** 107930