

1
2
3 **Assessing Source-Specific Irrigation Contributions to Cropping**
4 **Systems in the Central and Eastern US**
5
6

7 Lokendra S Rathore^{1,*}, Emily K Burchfield¹
8

9 ¹ Department of Environmental Sciences, Emory University, Atlanta, GA, United States of
10 America
11

12 Corresponding author: Lokendra S Rathore, lrathor@emory.edu
13

14 Keywords: irrigation water use, cropping systems, crop likelihood, irrigation expansion
15
16
17
18
19
20
21
22
23
24
25
26
27
28
29
30
31
32
33
34
35
36
37
38
39
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Abstract

Irrigation is a vital tool for boosting agricultural production and ensuring food security; yet the influence of irrigation on the cultivation geographies of major crops is insufficiently understood. We leverage explainable AI to quantify the contribution of groundwater and surface water irrigation application to crop likelihood—or the likelihood of seeing a specific crop in a specific place—for corn, soybeans, wheat, and sorghum across the Central and Eastern US. For the majority of counties, higher irrigation application rates are associated with increased cultivation of each crop. Higher surface water irrigation application is associated with higher wheat and soybean cultivation rates, while higher groundwater irrigation increases the likelihood of corn and sorghum cultivation. Notably, groundwater-induced crop likelihood increases with higher levels of non-renewable water use, highlighting the role of unsustainable groundwater extraction in shaping cultivation geographies. We explore the impact of irrigation expansion and collapse on cultivation geographies across the region and find that while expansion boosts crop likelihood for most crop-regions, irrigation collapse reduces the likelihood of at least one crop in more than 80% of counties. This research highlights the critical importance of irrigation access and irrigation source to cultivation outcomes in the Central and Eastern US. Our findings reveal irrigation hotspots where water source dependence shapes cultivation, and where shortfalls could destabilize production.

Introduction

In much of the world, irrigation is critical to agricultural production, enabling plants to grow in regions with limited natural water availability and by buffering against water deficit and extreme heat conditions (Zhu & Burney, 2022). About 20% of global croplands are irrigated, producing roughly 40% of the world's food (FAO, 2020). The global area equipped for irrigation expanded by 23% between 2000 and 2023, compared to 5% increase in global cropland areas over the same period (FAOSTAT, 2025), shaping cultivation choices (Ye et al., 2024) and boosting productivity in dryland regions (Zi et al., 2025). In the United States (US), around 15-20% of the irrigated land contributes to 40% of the agricultural production, and nearly half of the total crop sales value (Hrozencik, 2021; Ruess et al., 2023). As compared to rainfed systems, irrigated cropping systems exhibit reduced yield variability, more resistance to droughts, and higher crop productivity (Y. Chen et al., 2025; Frieler et al., 2017; Kukal & Irmak, 2020; Li & Troy, 2018; Tack et al., 2017; Wang et al., 2021; Zaveri & B. Lobell, 2019; Zhang et al., 2025).

Irrigated agriculture is currently facing a dual threat, as climate change affects both the supply and demand sides of water resources. Rising temperatures are expected to increase crop irrigation water requirements by raising the vapor pressure deficit (Williams & Abatzoglou, 2025). Moreover, crop water availability is increasingly at risk due to more severe droughts and compound heat-dry events (Gautam et al., 2023; Rastogi et al., 2023), degraded freshwater resources (Scholl et al., 2025), altered streamflow regimes (Brunner et al., 2020; Gupta et al., 2023), increased coastal groundwater contamination from saltwater intrusion (Zamrsky et al., 2024), and intense rainfall events that may deteriorate the surface water quality due to nutrient runoff (Skidmore et al., 2023). Another major concern for irrigated agriculture is the unsustainable withdrawal of freshwater resources, leading to widespread groundwater depletion (Scanlon et al., 2012a). Heavy reliance on unsustainable water use places irrigation systems at considerable risk. The High Plains aquifer in the Central US is already overexploited, and climate change is expected to further reduce its groundwater storage (Wu et al., 2020), raising concerns about long-term agricultural viability. Groundwater depletion in this region could undermine both the agricultural system and the regional economic development (Terrell et al., 2002). Therefore, assessing vulnerability and sustainability of irrigated agriculture is vital for understanding the potential outcomes of reduced or failed irrigation, given its important role in farmer livelihoods and regional food security.

This paper explores the role of irrigation in shaping regional cultivation geographies in the Central and Eastern US. To represent these cultivation patterns quantitatively, we define "crop likelihood" as the probability that a given crop is grown in a specific region, based on agro-environmental, socio-economic, and demographic variables. We leverage machine learning to quantify the source-specific (groundwater and surface water) contributions of irrigation to the crop likelihood of corn, soybeans, wheat, and sorghum—four crops that accounted for 57% of the total US crop sales in 2022 (*USDA/NASS QuickStats Ad-Hoc Query Tool*, 2025). We train random forest models with 68 variables to predict crop likelihood for each crop and use an explainable AI framework to quantify the contributions of surface water and groundwater application rates to cultivation possibilities.

Methods

Data and model

We simulate the crop likelihood for corn, soybeans, wheat, and sorghum for 38 Central and Eastern US states using crop-specific random forest models. We obtain crop distributions from the USDA's cropland data layer (CDL) at 30-meter resolution for 2008-2019 (*Cropland Data Layer*, 2025). A crop is considered likely to grow in a CDL pixel if it appears in more than two years during this period, and such pixels are assigned a value of 1 (otherwise 0). These binary values serve as the target variable in the random forest model. Then the predicted probability of a pixel being assigned 1 represents the likelihood of a crop.

The explanatory variables used in this study are broadly classified into biophysical and agricultural categories. The biophysical dataset includes climate, soil, and topography. The agricultural dataset comprises information on irrigation, farm management, farm inputs, economics, demographics, and farming-related infrastructure. In total, the models are trained on 68 variables: 25 biophysical and 43 agricultural (see Table S1 for details on all variables). Climate data consists of 17 various climatic indices obtained from WorldClim (Fick & Hijmans, 2017). Soil data, including percentages of silt, sand, clay, and gravel in the topsoil, bulk density, and cation exchange capacity, are extracted from the Harmonized World Soil Database (Food Agriculture Organization, 2012). Slope and elevation data are taken from the National Elevation Dataset (Gesch, 2007). Irrigation information includes crop-specific irrigation water use from (Ruess et al., 2024), which provides county estimates of crop-specific surface and groundwater withdrawal for irrigation from 2008 to 2020. We divide the irrigation withdrawals by cropland area to calculate the surface and groundwater irrigation rates (m³/acre). Management data include cover crop acres, percentage acres of conventional and no-till practices, number of organic farm operations, cattle inventory, and federal conservation program information with acres under conservation reserve program (CRP), and environmental quality incentives programs (EQIP). Farm inputs data include fertilizer amount and expenses, machinery, labor, and chemical expenses. Economic data include animal sales, share of rented or part-owned operations, small and mega farm sales, direct sales to retail and wholesale, percentage of corn and soybean used for biofuel, and crop insurance acres. We include demographic information in the model by incorporating urban-rural classification, the number of female and non-white producers, farm size, and the proportion of young and beginning farm producers. All temporal data between 2008 and 2019 are averaged to represent the mean agricultural conditions.

Irrigation's contribution to cultivation possibilities

We use SHAP (SHapley Additive exPlanations) values to quantify the contribution of surface and groundwater irrigation rates to crop likelihood in the Central and Eastern US (Lundberg & Lee, 2017). We use the *TreeExplainer* algorithm from the SHAP library, which computes exact Shapley values for tree-based models by exploiting their internal tree structure. It also fairly distributes feature contributions in the presence of correlated predictors, providing interpretable attributions (Lundberg et al., 2020). SHAP values are based on game theory principles and explain the

predictions of black-box machine learning models by attributing the contribution of each feature to a given model output. The random forest models have two irrigation variables- surface water irrigation rate (SWW) and groundwater irrigation rate (GWW). With SHAP, we obtain the contribution of the source-specific irrigation application rates in predicting the crop likelihood. A positive SHAP value indicates that existing irrigation increases the model-predicted crop likelihood in a county, whereas a negative SHAP value implies that irrigation decreases it. A SHAP value of zero means irrigation does not contribute to the prediction. The SHAP values are additive and can be aggregated across variables to obtain the grouped explanation. The sum of all SHAP values and the model's base prediction equals the final predicted crop likelihood. Thus, a positive irrigation SHAP value can be interpreted as irrigation pushing the prediction toward a higher crop likelihood, whereas a negative value represents irrigation pushing it toward a lower likelihood. The random forest models are run at the pixel scales, but the SHAP values are obtained at the county scale for two main reasons: i) the majority of agricultural variables, including irrigation data, are available at the county scale; and ii) due to computational constraints.

Irrigation expansion and collapse scenarios

To evaluate how changes in irrigation rate influence crop likelihood, we design a set of irrigation expansion and collapse scenarios. For the irrigation expansion scenario, groundwater and surface-water irrigation rates are systematically increased from their crop-specific observed minimum to maximum values. At each increment, we predict crop likelihood to quantify regional sensitivity to irrigation rate. In the irrigation collapse scenarios, we assess the vulnerability of crop likelihood to substantial reductions in irrigation. We examine two levels of collapse: complete collapse, simulated by setting both groundwater and surface-water irrigation rates to zero, and a 75% reduction, simulated by reducing irrigation rates by 75%.

Results

The random forest models perform well in predicting crop likelihood with accuracies for all crops above 0.86 (Table S2). The likelihood of corn and soybean shows a similar trend, both are more likely to grow in the Heartland, Northern Great Plains, Northern Crescent, Mississippi Portal, and Southern Seaboard regions, whereas wheat and sorghum exhibit higher likelihood in the Prairie Gateway (Figure 1). Here we follow the USDA Farm Resource Region (FRR) naming convention (see Figure S1). The crop likelihood values range from 0 to 1, where 0 represents the lowest and 1 the highest likelihood of growing a crop.

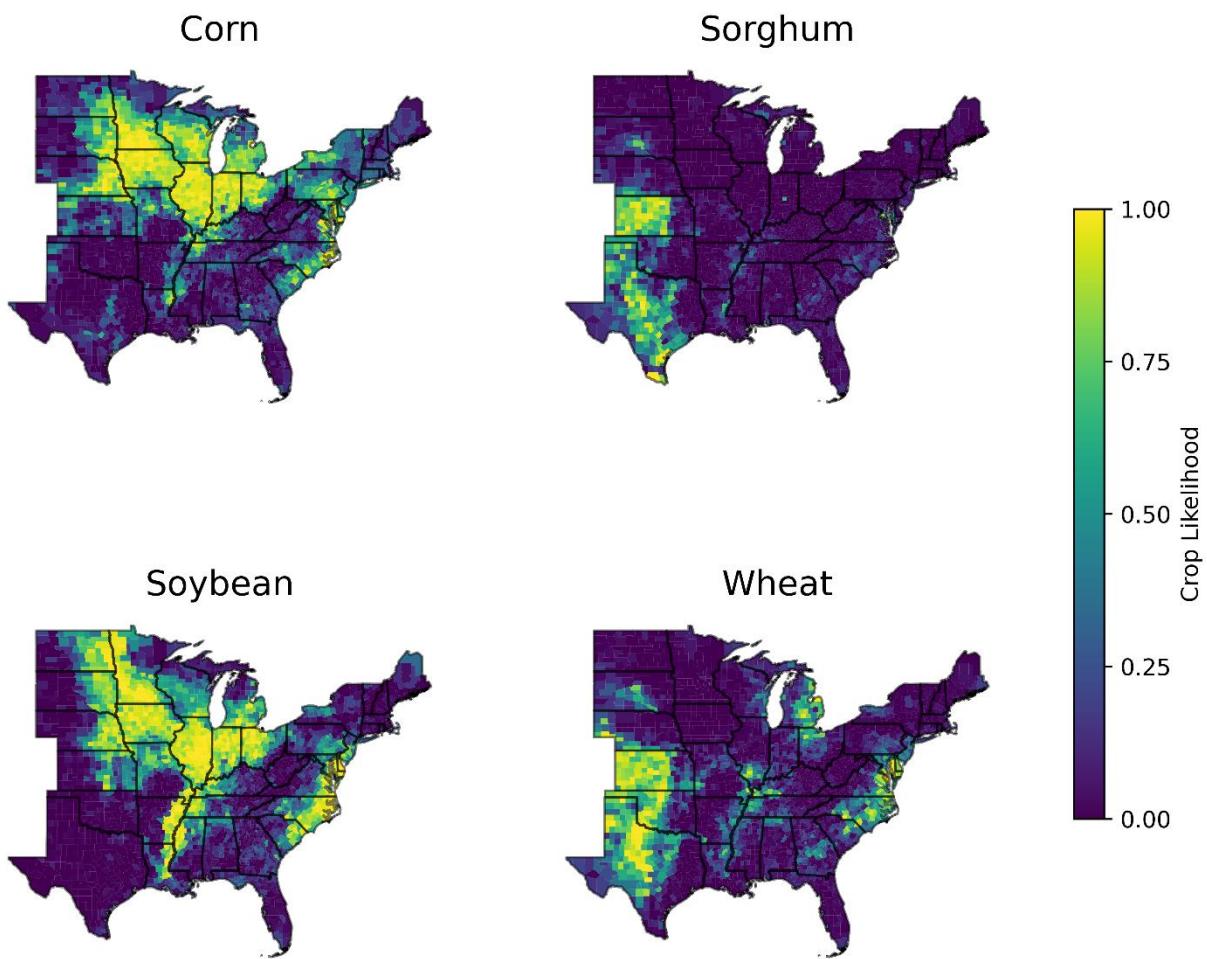


Figure 1. Spatial distribution of model-predicted crop likelihood of the four crops.

Irrigation's contribution to crop likelihood

Higher irrigation rates positively contribute to crop likelihood, as indicated by the distribution of SHAP values (Figure 2). This suggests that, for all four crops and across regions, higher irrigation rates are associated with a higher likelihood of cultivating each crop. For corn, soybeans, wheat, and sorghum, approximately 90%, 94%, 88% and 85% of the counties with the highest irrigation rates (top 25%) have positive SHAP values, respectively, suggesting that irrigation pushes towards high crop likelihood in these areas. In contrast, among the remaining counties (bottom 75%), only about 31%, 32%, 2% and 2% have positive SHAP values, implying that low-medium irrigation rates generally contribute negatively, pushing the prediction toward lower crop likelihood.

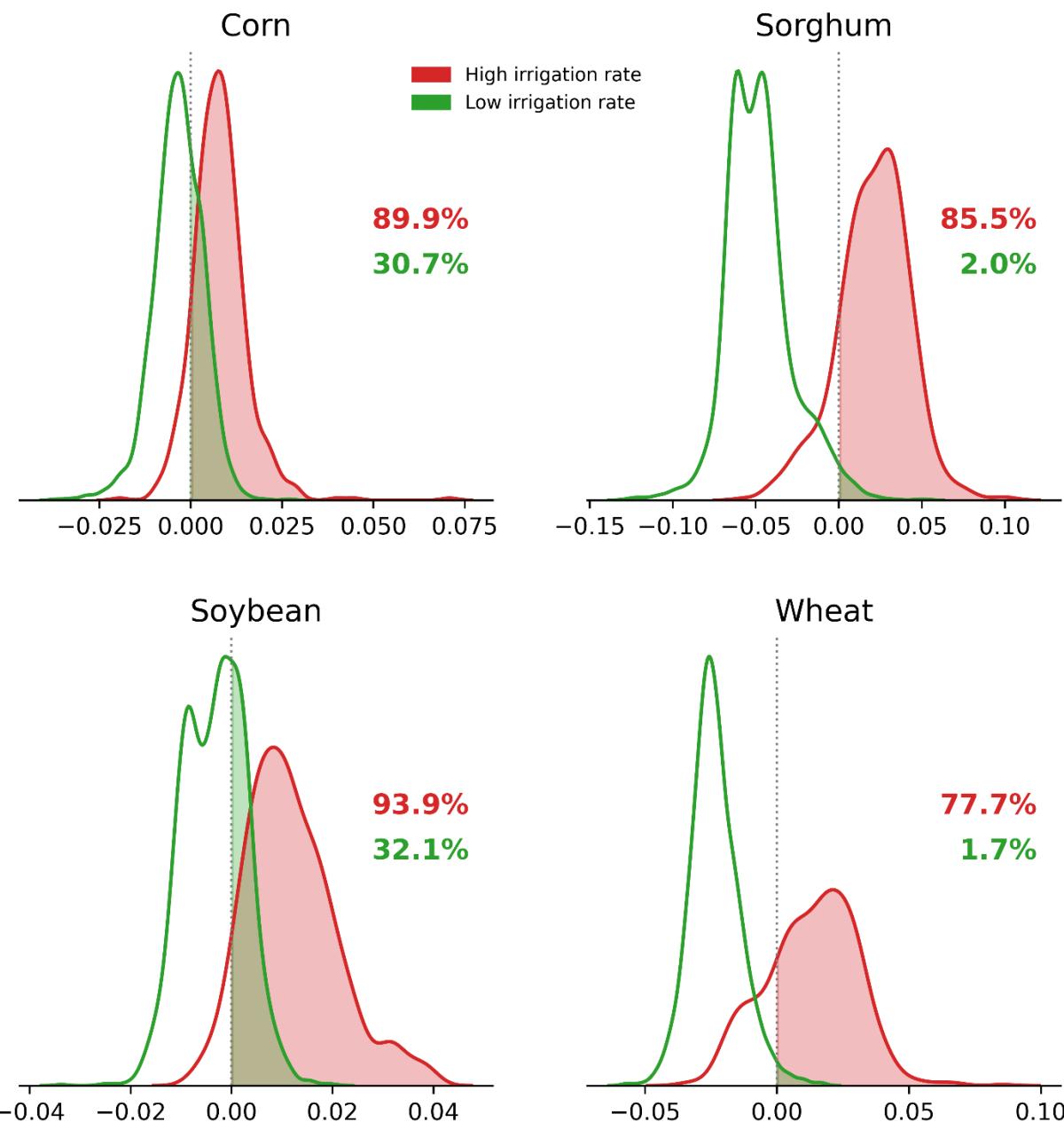


Figure 2. Distribution of county SHAP values for high irrigation (irrigation rate $> 75^{\text{th}}$ percentile; in red) and low irrigation (irrigation rate $\leq 75^{\text{th}}$ percentile; in green) counties. The irrigation rate is the combined rate of groundwater and surface water irrigation. Percentages indicate the proportion of counties with positive SHAP values within each irrigation category.

Next, we identify spatial patterns of source-specific irrigation influence on crop likelihood. Areas where high irrigation (surface water or groundwater) rates enhance the crop likelihood are shown in green, and areas with low irrigation rates, linked to reduced likelihood, are shown in red (Figure 3a). Counties where irrigation has little or no effect, i.e., where SHAP values fall below the 25th percentile for both positive and negative contributions, are depicted in gray. Negative SHAP values

suggest a negative irrigation impact on crop likelihood, possibly due to insufficient irrigation, excessive irrigation causing issues like waterlogging, or irrigation being less critical in high-rainfall regions. High groundwater withdrawal significantly contributes to the likelihood of corn cultivation in the Ogallala aquifer region, the Lake States (Minnesota, Wisconsin, and Michigan), and the Mississippi Delta regions, whereas surface water contributes mainly in the Southeast. Similarly, for soybeans, groundwater primarily boosts crop likelihood in Nebraska and the Mississippi Delta, while surface water is associated with increased soybean cultivation in the Southeast. Sorghum and wheat likelihood is increased by groundwater in the Great Plains region and by surface water in the Southeast. Conversely, inadequate irrigation application hinders the likelihood of corn and soybean in the Southern Great Plains and some counties in the Southeast and the Dakotas. For sorghum and wheat, low irrigation reduces the crop likelihood in the Midwest, Southeast, and the Northern Crescent. These are the regions where applying irrigation might increase the crop likelihood.

Interestingly, some counties exhibit high SHAP values despite having low irrigation rates (shown in blue in Figure 3a). Further analysis indicates the potentially mediating role of other agricultural and climatic variables. For example, for corn, counties with low groundwater withdrawal but positive SHAP values have higher average N-fertilizer application, dry-month precipitation, and chemical expenditures compared to counties with negative SHAP values (Figure S2). These counties also have a greater number of animal feed manufacturers, grain and oilseed milling facilities, fruit and vegetable processors, and dairy product manufacturers. In other words, favorable biophysical conditions and high agricultural inputs, and supportive infrastructure mitigate the negative contribution of low irrigation rates, highlighting the combined influence of multiple factors in determining cultivation geographies in a region.

Moreover, we use data on non-renewable groundwater withdrawal from Ruess et al. (2024) to examine its relationship with crop likelihood. Non-renewable withdrawals account for a substantial share of total groundwater use: 20% for corn, 3% for soybeans, 43% for wheat, and 48% for sorghum. Our results show that counties extracting non-renewable groundwater exhibit consistently higher SHAP values. Specifically, SHAP values for groundwater irrigation increase with the withdrawals drawn from non-renewable sources. On average, counties with non-renewable groundwater extraction have SHAP values that are 237% higher for corn, 391% for soybeans, 109% for wheat, and 104% for sorghum compared to counties using only renewable groundwater. This underscores the critical role of non-renewable groundwater in sustaining crop likelihood. Kansas, Nebraska, and Texas have the highest non-renewable groundwater withdrawals for corn; Kansas, Nebraska, and Arkansas for soybeans; and Kansas, Oklahoma, and Texas for wheat and sorghum.

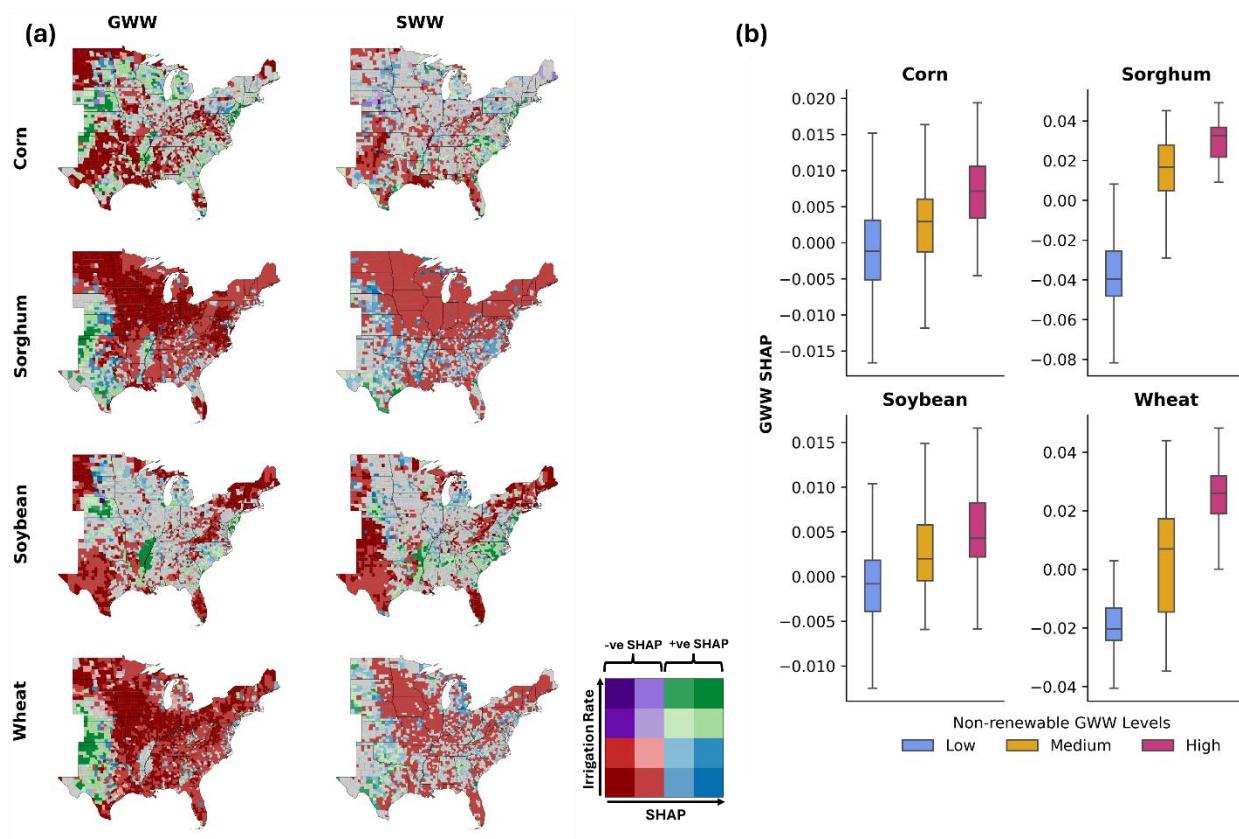


Figure 3. (a) The distribution of SHAP values and the actual irrigation rate (km^3/acre) from groundwater (GWW) and surface water (SWW) sources. SHAP values increase horizontally from left (-ve values) to right (+ve values) in the color scheme, while irrigation rates increase from bottom (low values) to top (high values). Higher SHAP values (both +ve and -ve) are depicted in darker colors. Counties with marginal absolute SHAP values are shown in gray, which implies no significant irrigation contribution towards crop likelihood prediction. (b) Boxplots show the GWW SHAP in counties with different levels of non-renewable GWW.

Groundwater irrigation enhances crop likelihood in a greater number of counties for corn and sorghum, while surface water irrigation emerged as a dominant source of irrigation for soybeans and wheat (Figure S3). Across the US, approximately 63% of counties show a greater SHAP value for GWW compared to SWW for corn, 55% for sorghum, 42% for soybeans, and 47% for wheat. The spatial distribution of these patterns varies across FRRs: Counties in Prairie Gateway, Northern Great Plains, and Northern Crescent exhibit a high fraction of counties where GWW SHAP dominates, whereas surface water withdrawal seems to be the major source in Southern Seaboard. For the Mississippi Portal region, groundwater's contribution exceeds for corn, wheat, and sorghum, while surface water contributes more for soybeans.

Irrigation expansion and crop likelihood

We perform the irrigation expansion scenario and aggregate the likelihood values at the FRR level to evaluate their regional sensitivities to irrigation application. The results show that increasing irrigation rates enhances the crop likelihood across all crops and FRRs, though the magnitude and

the pace of response vary by crop-region combination (Figure 4a). Sorghum shows the strongest and most rapid gains, with crop likelihood rising sharply even at relatively small irrigation increases, particularly in the Heartland, Northern Crescent, and Northern Great Plains. This indicates the high responsiveness and capacity of sorghum to thrive under relatively low irrigation application rates. Wheat also exhibits substantial sensitivity, with steady gains across most regions once irrigation surpasses mid-range levels. For corn and soybeans, responses seem more gradual, with the crop likelihood increasing the most in the Prairie Gateway and the Mississippi Portal (corn) and the Prairie Gateway and the Northern Great Plain (soybeans). In the Heartland, irrigation expansion results in little increase in the likelihood of corn and soybeans, and high irrigation rates even reduce the likelihood. This reflects that irrigation expansion provides minimal gains for corn and soybeans in the Heartland, as these crops are predominantly cultivated under rainfed conditions. These patterns underscore strong regional heterogeneity in irrigation-driven likelihood gains, highlighting sorghum and wheat as highly responsive to expanded irrigation in the semi-arid regions.

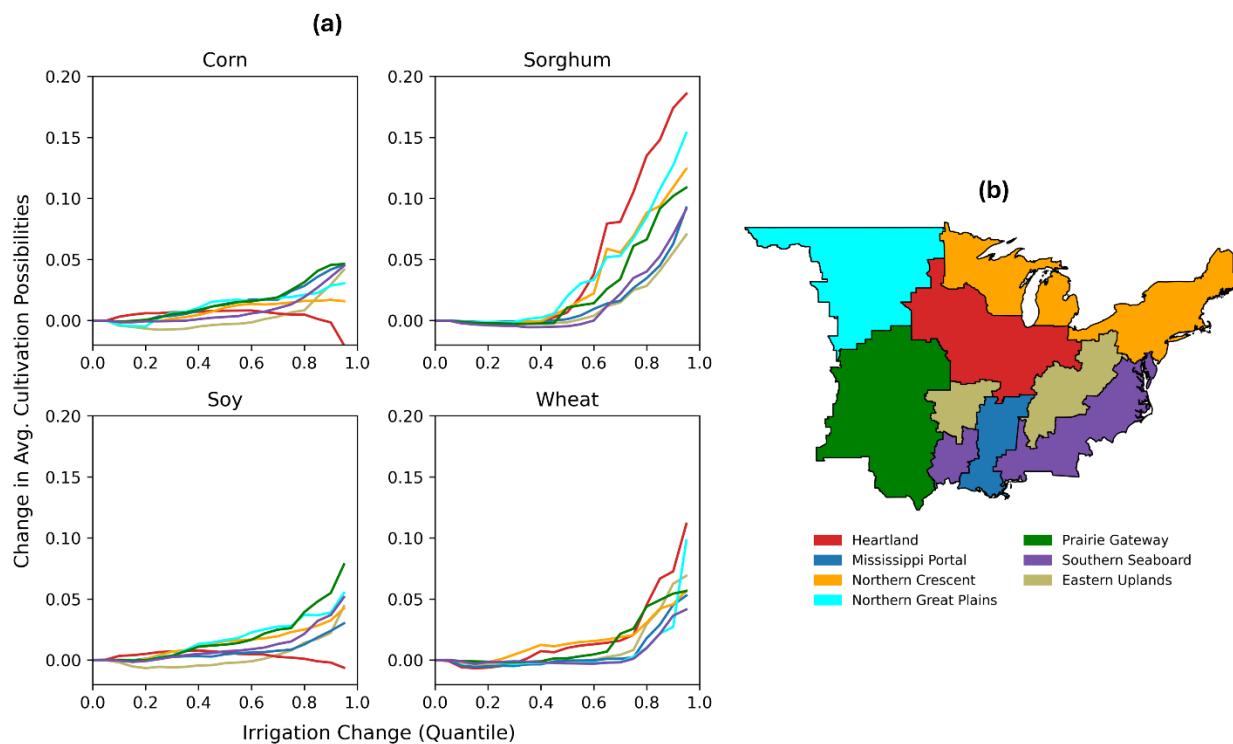


Figure 4. (a) Percent change in average crop likelihood across six major FRRs in the Central and Eastern US. The irrigation rates are adjusted from the lowest observed values to the highest observed values in an FRR, with x-axis values representing percentiles. (b) The farm resource regions map.

Impact of irrigation collapse on crop likelihood

Irrigation collapse leads to widespread declines in crop likelihood across major production regions (Figure 5). Under complete irrigation collapse, the average reductions are 7%, 6%, 11%, and 23% for corn, soybean, wheat, and sorghum, respectively, whereas under the 75% reduction scenario,

the average reductions are slightly smaller at 5%, 4%, 7%, and 11%. Sorghum experiences the most pronounced impact among all crops under both scenarios. Among counties with initial likelihood above 0.3, reductions occur in 64%, 65%, 70%, and 89% of counties for corn, soybean, wheat, and sorghum, respectively, under 100% collapse, and in 43%, 45%, 55%, and 71% of counties under 75% reduction. Overall, 82% of counties (68% under 75% reduction) with initial crop likelihood above 0.3 experience a reduction in at least one crop. The impact is particularly severe in counties with high cultivation potential (initial crop likelihood above 0.7), where 72%, 75%, 91%, and 99% of counties experience reductions under complete collapse, compared to 45%, 50%, 66%, and 77% of counties under 75% irrigation reduction, highlighting that irrigation loss most strongly affects regions already exhibiting high crop likelihood.

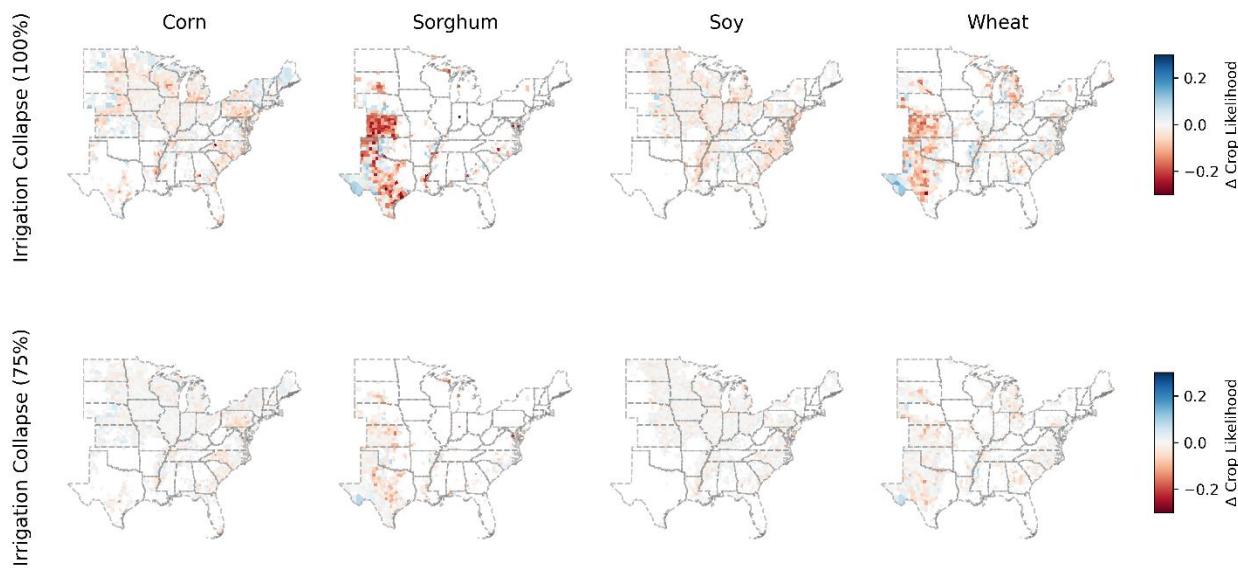


Figure 5. The difference in crop likelihood after complete irrigation collapse (top) and irrigation collapses by 75% (bottom).

Furthermore, we identify the crop-specific agriculturally important counties—those with the potential to destabilize national crop production—following the framework developed (Mehrabi & Ramankutty, 2019). These regions, commonly known as “breadbaskets,” are often destabilizing because they contribute to higher variance in production due to their substantial output and interannual variability. Adapting this approach to the US, we identify such destabilizing counties based on their influence on national crop production variance, as detailed in (Rathore, Kumar, Moftakhi, et al., 2024). These destabilizing counties are primarily concentrated in Iowa and Indiana for corn; Indiana and North Dakota for soybeans; Nebraska and Kansas for sorghum; and Kansas and Oklahoma for wheat (Figure S4). A complete irrigation collapse results in the reduction of crop likelihood in significant proportions of agriculturally important counties (Figure S5). Specifically, this impacts 45% of destabilizing counties for corn, 53% for soybeans, 60% for wheat, and 60% for sorghum. Moreover, the destabilizing counties where irrigation collapse reduces crop likelihood are situated in major crop-producing regions and accounted for 51%, 53%, 54%, and 44% of the mean national crop production for corn, soybeans, sorghum, and wheat, respectively, over the period 1970–2020. Consequently, irrigation collapse or threats to irrigation water

availability in these high-impact counties could substantially influence national crop production, potentially exacerbating production variability and threatening food security.

Discussion and conclusions

Cultivation geographies are shaped by a combination of biophysical, environmental, socio-economic, and policy-based constraints (Burchfield, 2022). Irrigation plays a critical role in crop production by increasing farmer profits and influencing regional cropping patterns. Our study shows that higher irrigation water availability enhances the likelihood of crop cultivation. High irrigation withdrawals from the Ogallala Aquifer support the cultivation of corn, sorghum, soybeans, and wheat. Irrigation in the Lower Mississippi River Delta also enhances corn, soybeans, and sorghum production. We analyze the relative contributions of groundwater and surface water irrigation sources, which vary in dominance across regions and crops (Table 2). The study highlights that with higher groundwater contributions, the use of non-renewable groundwater also increases, especially in the High Plains aquifers. Earlier studies similarly emphasize unsustainable water use in these regions (Gleeson et al., 2012; Marston et al., 2015; Rosa et al., 2019; Scanlon et al., 2012b).

Table 2: Fraction of counties where groundwater contributes more than surface water irrigation sources.

Region	Corn	Sorghum	Soybean	Wheat
Heartland	0.61	0.64	0.48	0.09
Mississippi Portal	0.69	0.62	0.40	0.68
Northern Crescent	0.76	0.40	0.47	0.33
Northern Great Plains	0.77	0.45	0.62	0.42
Prairie Gateway	0.74	0.83	0.53	0.82
Southern Seaboard	0.45	0.35	0.25	0.29

Irrigation expansion influences the regional crop likelihood, with sorghum and wheat cultivation potential showing greater sensitivity compared to corn and soybean. The difference is likely due to their initial lower crop likelihood and greater scope of expansion in regions such as the Heartland, Northern Crescent, and Prairie Gateway, whereas corn and soybean already dominate these areas with high likelihood. Notably, previous studies reported that corn shows more responsiveness to irrigation than sorghum in western Kansas (Lamm et al., 2007; Stone et al., 1996). However, these studies focused on yield outcomes, whereas our analysis examines crop likelihood, which reflects the broader potential for crop cultivation, of which yield is one of the contributing factors. Other agricultural, socio-economic, and policy-based factors also play critical roles. Our findings suggest that irrigation expansion can enhance the cultivation potential of sorghum in the Heartland and Northern Crescent regions. Importantly, high crop likelihood for sorghum does not imply a reduction or replacement of corn and soybean. In fact, sorghum could

serve as a companion crop alongside corn under supplemental irrigation, consistent with findings from (Klocke et al., 2012).

In the US, major aquifer systems such as the High Plains, Central Valley, and Mississippi Embayment have been intensively exploited to support irrigated agriculture. US crop production and food trade rely heavily on non-renewable groundwater, leaving them vulnerable as groundwater levels decline (Gumidyala et al., 2020). Our analysis shows that non-renewable groundwater contributes significantly to the crop likelihood. In regions dominated by non-renewable groundwater, irrigation contributions are roughly three times higher than in renewable-only counties for corn, five times higher for soybeans, and about twice as high for wheat and sorghum. Limiting the non-renewable groundwater use could reduce the national production of corn, soybeans, and wheat by approximately 20%, 6% and 25%, respectively (Lopez et al., 2022). We performed an irrigation collapse scenario to highlight the regions that are most vulnerable to the depletion of irrigation sources. Our findings suggest that with irrigation collapse, around 82% of the counties would experience a reduction in the likelihood of at least one of the four crops considered. The impacts are particularly severe in the Southern Great Plains, and some parts of the Southeast and Upper Midwest. Moreover, irrigation collapse could adversely impact the national crop production by reducing crop likelihood in the destabilizing regions.

We use random forest, which is a black-box machine learning model, and SHAP helps with interpretability by attributing each prediction to its input features. However, SHAP results come with caveats. Because the SHAP approach uses the model structure, its reliability depends on model accuracy. In our case, all models achieved accuracies of more than 86%, which lends confidence to the SHAP-based explanations. Nevertheless, both random forest and SHAP are data-driven approaches and are therefore subject to the uncertainties in data collection, imputation, and processing, which propagate to the model output. Additionally, the random forest itself suffers from structural uncertainties. Future research should explore grounded, place-based, AI-based approaches that incorporate stakeholder knowledge and real-world agricultural decision-making to further improve model reliability and reduce uncertainties. Another limitation arises from the mismatch in spatial scales: while our random forest models were trained at the pixel level, several agricultural variables are only available at the county level. We assumed uniform values across all pixels within a county, which may overlook the within-county variability of the management, socio-economic, and policy variables. Although this assumption introduces potential bias, it enables the integration of high-resolution CDL and biophysical data. The use of more pixels also increased the training sample size, thus improving model robustness.

Irrigation is a vital tool to increase food production and is associated with improved well-being of farming communities and better child nutrition outcomes (BenYishay et al., 2024; Mehta et al., 2025; Okyere & Usman, 2021). Irrigation expansion using small-scale water storage infrastructure can sustainably feed an additional 300 million people under 3 °C warmer conditions (Rosa et al., 2020). However, unsustainable irrigation expansion may exacerbate water scarcity in urban areas (Rathore, Kumar, Hanasaki, et al., 2024). Globally, irrigation expansion increased evapotranspiration, which was not compensated by precipitation, resulting in a net loss of water (Yao et al., 2025). Irrigation-induced landscape changes and monocultural farming practices can

affect the natural bird habitats and farmland biodiversity (Benton et al., 2003; Cabodevilla et al., 2022; Giralt et al., 2021). In some regions, irrigation has been linked to soil salinity (Aldakheel, 2011; Mohanavelu et al., 2021) and changes in regional climate patterns (Chauhan et al., 2023; L. Chen & Dirmeyer, 2019). In the study, we assumed simplistic irrigation scenarios; however, irrigation expansion should be carefully monitored, and its comprehensive impacts on local and regional ecosystems need to be systematically assessed.

In conclusion, this study demonstrates that irrigation is a critical driver shaping regional crop likelihood. Using an explainable AI approach (SHAP), we provide new insights into regional dependencies and sensitivities to groundwater and surface water irrigation. Greater access to irrigation water incentivizes farmers to cultivate particular crops, and thus, irrigation expansion generally increases crop likelihood across most farm resource regions. Nonetheless, changes in other factors such as policy, subsidies, management practices, on-farm tech, and labor availability also play an important role in crop selection. We highlight the reliance of current cropping systems on unsustainable groundwater, which underscores the need for careful planning of irrigation expansion. If not properly managed, unsustainable irrigation expansion can degrade local and downstream water resources, with far-reaching consequences on ecosystems and communities. Our results reveal that several agriculturally important regions are highly vulnerable to irrigation water depletion, with broader implications for national food security. Overall, these results support the development of policies that better align agricultural incentives with regional water constraints and focus attention on important but water-vulnerable regions to safeguard long-term food system resilience.

Acknowledgement

EB acknowledges support from the National Science Foundation (Award 2307271, DISES program). We also thank Marco Ferro for providing constructive feedback on this study.

Competing Interests

The authors declare no competing interests.

References

- Aldakheel, Y. Y. (2011). Assessing NDVI Spatial Pattern as Related to Irrigation and Soil Salinity Management in Al-Hassa Oasis, Saudi Arabia. *Journal of the Indian Society of Remote Sensing*, 39(2), 171–180. <https://doi.org/10.1007/s12524-010-0057-z>
- Benton, T. G., Vickery, J. A., & Wilson, J. D. (2003). *Farmland biodiversity: Is habitat heterogeneity the key?* [https://www.cell.com/trends/ecology-evolution/abstract/S0169-5347\(03\)00011-9](https://www.cell.com/trends/ecology-evolution/abstract/S0169-5347(03)00011-9)
- BenYishay, A., Sayers, R., Singh, K., Goodman, S., Walker, M., Traore, S., Rauschenbach, M., & Noltze, M. (2024). Irrigation strengthens climate resilience: Long-term evidence from Mali using satellites and surveys. *PNAS Nexus*, 3(2), pgae022. <https://doi.org/10.1093/pnasnexus/pgae022>
- Brunner, M. I., Melsen, L. A., Newman, A. J., Wood, A. W., & Clark, M. P. (2020). Future streamflow regime changes in the United States: Assessment using functional classification. *Hydrology and Earth System Sciences*, 24(8), 3951–3966. <https://doi.org/10.5194/hess-24-3951-2020>
- Burchfield, E. K. (2022). Shifting cultivation geographies in the Central and Eastern US. *Environmental Research Letters*, 17(5), 054049. <https://doi.org/10.1088/1748-9326/ac6c3d>
- Cabodevilla, X., Wright, A. D., Villanua, D., Arroyo, B., & Zipkin, E. F. (2022). The implementation of irrigation leads to declines in farmland birds. *Agriculture, Ecosystems & Environment*, 323, 107701. <https://doi.org/10.1016/j.agee.2021.107701>
- Chauhan, T., Devanand, A., Roxy, M. K., Ashok, K., & Ghosh, S. (2023). River interlinking alters land-atmosphere feedback and changes the Indian summer monsoon. *Nature Communications*, 14(1), 5928. <https://doi.org/10.1038/s41467-023-41668-x>
- Chen, L., & Dirmeyer, P. A. (2019). Global observed and modelled impacts of irrigation on surface temperature. *International Journal of Climatology*, 39(5), 2587–2600. <https://doi.org/10.1002/joc.5973>
- Chen, Y., Wang, Y., Wu, C., Rosa Ferraz Jardim, A. M. da, Fang, M., Yao, L., Liu, G., Xu, Q., Chen, L., & Tang, X. (2025). Drought-induced stress on rainfed and irrigated agriculture: Insights from multi-

- 1
2
3 source satellite-derived ecological indicators. *Agricultural Water Management*, 307, 109249.
4
5 <https://doi.org/10.1016/j.agwat.2024.109249>
- 6
7 *Cropland Data Layer*. (2025). [Dataset]. National Agricultural Statistics Service, Department of
8 Agriculture. <https://catalog.data.gov/dataset/cropscape-cropland-data-layer>
- 9
10 FAO. (2020). The state of food and agriculture 2020. Overcoming water challenges in agriculture. *Food*
11
12 and Agriculture Organization of the United Nations.
- 13
14 FAOSTAT. (2025). <https://www.fao.org/faostat/en/#data/RL>
- 15
16 Fick, S. E., & Hijmans, R. J. (2017). WorldClim 2: New 1-km spatial resolution climate surfaces for
17 global land areas. *International Journal of Climatology*, 37(12), 4302–4315.
18
19 <https://doi.org/10.1002/joc.5086>
- 20
21 Food Agriculture Organization. (2012). *Harmonized world soil database v1.2 | FAO SOILS*
22
23 PORTAL | Food and Agriculture Organization of the United Nations [Dataset].
24
25 <https://www.fao.org/soils-portal/data-hub/soil-maps-and-databases/harmonized-world-soil-database-v12/en/>
- 26
27 Frieler, K., Schauberger, B., Arneth, A., Balkovič, J., Chryssanthacopoulos, J., Deryng, D., Elliott, J.,
28 Folberth, C., Khabarov, N., Müller, C., Olin, S., Pugh, T. A. M., Schaphoff, S., Schewe, J.,
29 Schmid, E., Warszawski, L., & Levermann, A. (2017). Understanding the weather signal in
30 national crop-yield variability. *Earth's Future*, 5(6), 605–616.
31
32 <https://doi.org/10.1002/2016EF000525>
- 33
34 Gautam, S., Mishra, U., Scown, C. D., & Ghimire, R. (2023). Increased drought and extreme events over
35 continental United States under high emissions scenario. *Scientific Reports*, 13(1), 21503.
36
37 <https://doi.org/10.1038/s41598-023-48650-z>
- 38
39 Gesch, D. (2007). *The National Elevation Dataset*.
- 40
41 Giralt, D., Pantoja, J., Morales, M. B., Traba, J., & Bota, G. (2021). *Frontiers | Landscape-Scale Effects*
42
43 of Irrigation on a Dry Cereal Farmland Bird Community.
- 44
45 <https://doi.org/10.3389/fevo.2021.611563>

- 1
2
3 Gleeson, T., Wada, Y., Bierkens, M. F. P., & van Beek, L. P. H. (2012). Water balance of global aquifers
4 revealed by groundwater footprint. *Nature*, 488(7410), 197–200.
5
6 https://doi.org/10.1038/nature11295
7
8 Gumidyala, S., Ruess, P. J., Konar, M., Marston, L., Dalin, C., & Wada, Y. (2020). Groundwater
9 Depletion Embedded in Domestic Transfers and International Exports of the United States. *Water*
10
11 Resources Research, 56(2), e2019WR024986. https://doi.org/10.1029/2019WR024986
12
13 Gupta, A., Carroll, R. W. H., & McKenna, S. A. (2023). Changes in streamflow statistical structure across
14 the United States due to recent climate change. *Journal of Hydrology*, 620, 129474.
15
16 https://doi.org/10.1016/j.jhydrol.2023.129474
17
18 Hrozencik, R. A. (2021). *Trends in U.S. Irrigated Agriculture: Increasing Resilience Under Water Supply*
19
20 Scarcity
- (SSRN Scholarly Paper No. 3996325). Social Science Research Network.
-
- 21
-
- 22 https://doi.org/10.2139/ssrn.3996325
-
- 23
-
- 24 Klocke, N., Currie, R., Tomsicek, D., & Koehn, J. (2012). Sorghum yield response to deficit irrigation.
-
- 25
-
- 26 Transactions of the ASABE, 55(3), 947–955.
-
- 27
-
- 28 Kukal, M. S., & Irmak, S. (2020). Impact of irrigation on interannual variability in United States
-
- 29 agricultural productivity.
- Agricultural Water Management*
- , 234, 106141.
-
- 30
-
- 31 https://doi.org/10.1016/j.agwat.2020.106141
-
- 32
-
- 33 Kumar, S., Merwade, V., Rao, P. S. C., & Pijanowski, B. C. (2013). Characterizing Long-Term Land
-
- 34 Use/Cover Change in the United States from 1850 to 2000 Using a Nonlinear Bi-analytical
-
- 35 Model.
- AMBIO*
- , 42(3), 285–297. https://doi.org/10.1007/s13280-012-0354-6
-
- 36
-
- 37 Lamm, F., Stone, L., & O'brien, D. (2007). Crop production and economics in Northwest Kansas as
-
- 38 related to irrigation capacity.
- Applied Engineering in Agriculture*
- , 23(6), 737–745.
-
- 39
-
- 40 Li, X., & Troy, T. J. (2018). Changes in rainfed and irrigated crop yield response to climate in the western
-
- 41 US.
- Environmental Research Letters*
- , 13(6), 064031. https://doi.org/10.1088/1748-9326/aac4b1
-
- 42
-
- 43 Lopez, J. R., Winter, J. M., Elliott, J., Ruane, A. C., Porter, C., Hoogenboom, G., Anderson, M., & Hain,
-
- 44 C. (2022). Sustainable Use of Groundwater May Dramatically Reduce Irrigated Production of
-
- 45
-
- 46
-
- 47
-
- 48
-
- 49
-
- 50
-
- 51
-
- 52
-
- 53
-
- 54
-
- 55
-
- 56
-
- 57
-
- 58
-
- 59
-
- 60

- 1
2
3 Maize, Soybean, and Wheat. *Earth's Future*, 10(1), e2021EF002018.
4
5 <https://doi.org/10.1029/2021EF002018>
- 6
7 Lundberg, S. M., Erion, G., Chen, H., DeGrave, A., Prutkin, J. M., Nair, B., Katz, R., Himmelfarb, J.,
8
9 Bansal, N., & Lee, S.-I. (2020). From local explanations to global understanding with explainable
10 AI for trees. *Nature Machine Intelligence*, 2(1), 56–67. <https://doi.org/10.1038/s42256-019-0138-9>
- 11
12 Lundberg, S. M., & Lee, S.-I. (2017). A Unified Approach to Interpreting Model Predictions. *Advances in*
13
14 *Neural Information Processing Systems*, 30.
15
16 <https://proceedings.neurips.cc/paper/2017/hash/8a20a8621978632d76c43dfd28b67767-Abstract.html>
- 17
18 Marston, L., Konar, M., Cai, X., & Troy, T. J. (2015). Virtual groundwater transfers from overexploited
19 aquifers in the United States. *Proceedings of the National Academy of Sciences*, 112(28), 8561–
20 8566. <https://doi.org/10.1073/pnas.1500457112>
- 21
22 Mehrabi, Z., & Ramankutty, N. (2019). Synchronized failure of global crop production. *Nature Ecology*
23
24 & Evolution
- 25 *, 3(5)*, Article 5. <https://doi.org/10.1038/s41559-019-0862-x>
- 26
27 Mehta, P., Muller, M., Niles, M. T., & Davis, K. F. (2025). Child diet diversity and irrigation expansion in
28 the global south. *Nature Sustainability*, 8(8), 905–913. <https://doi.org/10.1038/s41893-025-01584-y>
- 29
30 Mohanavelu, A., Naganna, S. R., & Al-Ansari, N. (2021). Irrigation Induced Salinity and Sodicity
31 Hazards on Soil and Groundwater: An Overview of Its Causes, Impacts and Mitigation Strategies.
32
33 *Agriculture*, 11(10), 983. <https://doi.org/10.3390/agriculture11100983>
- 34
35 Okyere, C. Y., & Usman, M. A. (2021). The impact of irrigated agriculture on child nutrition outcomes in
36 southern Ghana. *Water Resources and Economics*, 33, 100174.
- 37
38 <https://doi.org/10.1016/j.wre.2020.100174>
- 39
40 Potapov, P., Turubanova, S., Hansen, M. C., Tyukavina, A., Zalles, V., Khan, A., Song, X.-P., Pickens, A.,
41 Shen, Q., & Cortez, J. (2022). Global maps of cropland extent and change show accelerated
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

- cropland expansion in the twenty-first century. *Nature Food*, 3(1), 19–28.
- <https://doi.org/10.1038/s43016-021-00429-z>
- Rastogi, D., Trok, J., Depsky, N., Monier, E., & Jones, A. (2023). Historical evaluation and future projections of compound heatwave and drought extremes over the conterminous United States in CMIP6*. *Environmental Research Letters*, 19(1), 014039. <https://doi.org/10.1088/1748-9326/ad0efe>
- Rathore, L. S., Kumar, M., Hanasaki, N., Mekonnen, M. M., & Raghav, P. (2024). Water scarcity challenges across urban regions with expanding irrigation. *Environmental Research Letters*, 19(1), 014065. <https://doi.org/10.1088/1748-9326/ad178a>
- Rathore, L. S., Kumar, M., Moftakhari, H., & Ganguli, P. (2024). Divergent changes in crop yield loss risk due to droughts over time in the US. *Environmental Research Letters*, 19(11), 114008.
- Rosa, L., Chiarelli, D. D., Sangiorgio, M., Beltran-Peña, A. A., Rulli, M. C., D'Odorico, P., & Fung, I. (2020). Potential for sustainable irrigation expansion in a 3 °C warmer climate. *Proceedings of the National Academy of Sciences*, 117(47), 29526–29534.
<https://doi.org/10.1073/pnas.2017796117>
- Rosa, L., Chiarelli, D. D., Tu, C., Rulli, M. C., & D'Odorico, P. (2019). Global unsustainable virtual water flows in agricultural trade. *Environmental Research Letters*, 14(11), 114001.
<https://doi.org/10.1088/1748-9326/ab4bfc>
- Ruess, P. J., Konar, M., Wanders, N., & Bierkens, M. (2023). Irrigation by Crop in the Continental United States From 2008 to 2020. *Water Resources Research*, 59(2), e2022WR032804.
<https://doi.org/10.1029/2022WR032804>
- Ruess, P. J., Konar, M., Wanders, N., & Bierkens, M. F. P. (2024). Total irrigation by crop in the Continental United States from 2008 to 2020. *Scientific Data*, 11(1), 395.
<https://doi.org/10.1038/s41597-024-03244-w>
- Scanlon, B. R., Faunt, C. C., Longuevergne, L., Reedy, R. C., Alley, W. M., McGuire, V. L., & McMahon, P. B. (2012a). Groundwater depletion and sustainability of irrigation in the US High Plains and

- 1
2
3 Central Valley. *Proceedings of the National Academy of Sciences*, 109(24), 9320–9325.
4
5 <https://doi.org/10.1073/pnas.1200311109>
6
7 Scanlon, B. R., Faunt, C. C., Longuevergne, L., Reedy, R. C., Alley, W. M., McGuire, V. L., & McMahon,
8 P. B. (2012b). Groundwater depletion and sustainability of irrigation in the US High Plains and
9 Central Valley. *Proceedings of the National Academy of Sciences*, 109(24), 9320–9325.
10
11 <https://doi.org/10.1073/pnas.1200311109>
12
13 Scholl, M. A., McCabe, G. J., Olson, C. G., & Powlen, K. (2025). Climate change and future water
14 availability in the United States. In *Professional Paper* (Nos. 1894-E). U.S. Geological Survey.
15
16 <https://doi.org/10.3133/pp1894E>
17
18 Skidmore, M., Andarge, T., & Foltz, J. (2023). The impact of extreme precipitation on nutrient runoff.
19
20 *Journal of the Agricultural and Applied Economics Association*, 2(4), 769–785.
21
22 <https://doi.org/10.1002/jaa2.90>
23
24 Stone, L. R., Schlegel, A. J., Gwin, R. E., & Khan, A. H. (1996). Response of corn, grain sorghum, and
25 sunflower to irrigation in the High Plains of Kansas. *Agricultural Water Management*, 30(3),
26 251–259. [https://doi.org/10.1016/0378-3774\(95\)01226-5](https://doi.org/10.1016/0378-3774(95)01226-5)
27
28 Tack, J., Barkley, A., & Hendricks, N. (2017). Irrigation offsets wheat yield reductions from warming
29 temperatures. *Environmental Research Letters*, 12(11), 114027. <https://doi.org/10.1088/1748-9326/aa8d27>
30
31 Terrell, B. L., Johnson, P. N., & Segarra, E. (2002). Ogallala aquifer depletion: Economic impact on the
32 Texas high plains. *Water Policy*, 4(1), 33–46. [https://doi.org/10.1016/S1366-7017\(02\)00009-0](https://doi.org/10.1016/S1366-7017(02)00009-0)
33
34 USDA/NASS *QuickStats Ad-hoc Query Tool*. (2025). <https://quickstats.nass.usda.gov/>
35
36 Wang, X., Müller, C., Elliot, J., Mueller, N. D., Ciais, P., Jägermeyr, J., Gerber, J., Dumas, P., Wang, C.,
37 Yang, H., Li, L., Deryng, D., Folberth, C., Liu, W., Makowski, D., Olin, S., Pugh, T. A. M.,
38 Reddy, A., Schmid, E., ... Piao, S. (2021). Global irrigation contribution to wheat and maize
39 yield. *Nature Communications*, 12(1), 1235. <https://doi.org/10.1038/s41467-021-21498-5>
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

- 1
2
3 Williams, E. L., & Abatzoglou, J. T. (2025). Climate Change Increases Evaporative and Crop Irrigation
4 Demand in North America. *Earth's Future*, 13(7), e2025EF005931.
5
6 https://doi.org/10.1029/2025EF005931
7
8 Wu, W.-Y., Lo, M.-H., Wada, Y., Famiglietti, J. S., Reager, J. T., Yeh, P. J.-F., Ducharne, A., & Yang, Z.-L.
9 (2020). Divergent effects of climate change on future groundwater availability in key mid-latitude
10 aquifers. *Nature Communications*, 11(1), 3710. https://doi.org/10.1038/s41467-020-17581-y
11
12 Yao, Y., Thiery, W., Ducharne, A., Cook, B., Ding, A., Hertog, S. D., Sieber, P., Aas, K., Arboleda-
13 Obando, P., Colin, J., Costantini, M., Decharme, B., Lawrence, D., Lawrence, P., Leung, L. R.,
14 Lo, M.-H., Devaraju, N., Wu, R.-J., Zhou, T., ... Seneviratne, S. (2025). *Irrigation-induced land*
15 *water depletion aggravated by climate change*. Research Square. https://doi.org/10.21203/rs.3.rs-
16 6170876/v1
17
18 Ye, S., Cao, P., & Lu, C. (2024). Annual time-series 1 km maps of crop area and types in the
19 conterminous US (CropAT-US): Cropping diversity changes during 1850–2021. *Earth System*
20 *Science Data*, 16(7), 3453–3470. https://doi.org/10.5194/essd-16-3453-2024
21
22 Zamrsky, D., Oude Essink, G. H. P., & Bierkens, M. F. P. (2024). Global Impact of Sea Level Rise on
23 Coastal Fresh Groundwater Resources. *Earth's Future*, 12(1), e2023EF003581.
24
25 https://doi.org/10.1029/2023EF003581
26
27 Zaveri, E., & B. Lobell, D. (2019). The role of irrigation in changing wheat yields and heat sensitivity in
28 India. *Nature Communications*, 10(1), 4144. https://doi.org/10.1038/s41467-019-12183-9
29
30 Zhang, L., Bai, G., Evett, S. R., Colaizzi, P. D., Xue, Q., Marek, G., Dhungel, R., Zhao, H., Wan, N., &
31 Lin, X. (2025). Increased irrigation could mitigate future warming-induced maize yield losses in
32 the Ogallala Aquifer. *Communications Earth & Environment*, 6(1), 483.
33
34 https://doi.org/10.1038/s43247-025-02459-y
35
36 Zhu, P., & Burney, J. (2022). Untangling irrigation effects on maize water and heat stress alleviation using
37 satellite data. *Hydrology and Earth System Sciences*, 26(3), 827–840.
38
39 https://doi.org/10.5194/hess-26-827-2022
40
41
42
43
44
45
46
47
48
49
50
51
52
53
54
55
56
57
58
59
60

Zi, S., Li, Y., Zhang, J., Hou, C., Lin, H., Xu, Z., Sang, S., Dong, J., & Fu, B. (2025). The biophysical and crop yield effects of irrigation and their changes in China's drylands. *Agricultural Water Management*, 313, 109471. <https://doi.org/10.1016/j.agwat.2025.109471>