

THESIS

IRRIGATED CROP YIELDS REVEAL DISTINCT INFLUENCES OF HEAT AND
MOISTURE

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ABSTRACT

IRRIGATED CROP YIELDS REVEAL DISTINCT INFLUENCES OF HEAT AND MOISTURE

Climate change presents a growing challenge to global food systems in addition to challenges to human and natural ecosystem health. While statistical crop models offer insights into how rising temperatures affect crop yield, a complete understanding of projected impacts has been limited by often-simplified assumptions about the independence of temperature and water stress. Here, we comprehensively analyze the covariance between commonly used predictors in statistical crop models. Using paired rainfed and irrigated yield observations across the US, we are able to control for the effects of water availability and independently evaluate the influence of temperature on yields. We find that temperature-based predictors often absorb the effects of water stress, inflating their apparent importance in statistical yield models. These findings have implications for the magnitude of projected yield damages and advance our understanding of the agricultural consequences of climate change.

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CHAPTER 1: INTRODUCTION

The global food system now operates under increasing pressure from climate change. Rising global mean temperatures, shifting precipitation patterns, and the increasing frequency of extreme weather events are already measurably reducing agricultural productivity worldwide (IPCC, 2023). A superposed epoch analysis of data from 1964 to 2007, found that droughts and extreme heat caused an average national per-disaster cereal production loss of 9–10% globally; however, this impact was significantly more severe in the technically developed agricultural systems of North America, Europe, and Australasia, which suffered an average production deficit of 19.9% (Lesk et al., 2016). These observed losses reflect a climate that has warmed by roughly 1°C above pre-industrial levels, and far greater warming is projected before the century's end (Kim et al., 2023). The IPCC has highlighted temperature thresholds exceeding 30°C as acutely harmful to both plants and animals (Seneviratne et al., 2021). This increased frequency of extreme heat events across major agricultural regions has prompted scientific and public attention toward heat as the primary driver of yield decline (Seneviratne et al., 2021).

The scale of the challenges to the global food system is amplified by rapidly growing demand. World population is projected to reach nearly 10 billion by 2050, and rising incomes in developing countries are shifting diets toward more calorie- and resource-intensive foods (Searchinger, 2019). Population growth alone is expected to increase global food demand by 35–56% between 2010 and 2050 (van Dijk et al., 2021). The UN Food and Agriculture Organization estimates that meeting this demand will require producing approximately 50% more food by 2050 relative to current output (FAO, 2018). However, roughly 52% of agricultural land is already classified as degraded, and climate change is expected to further reduce the suitability

and productivity of existing cropland in the world's current breadbaskets (Food and Agriculture Organization of the United Nations, n.d.).

The magnitude of projected climate-driven changes in crop yields varies across analyses but may be severe (Jägermeyr et al., 2021; Schlenker & Roberts, 2009). Under high-emission scenarios, the United States (U.S.) maize, soybean, and wheat yields could decline by 30–82% by century's end if growing regions remain fixed and adaptation is limited (Schlenker & Roberts, 2009). Globally, maize faces projected losses of 26.1%, wheat 28.5%, and soybean 36.8% under RCP 8.5, with damages most severe in current breadbaskets, including the US Maize Belt and China (Hultgren et al., 2025). Every additional degree Celsius of global warming is estimated to reduce global food production capacity by approximately 4.4% of current daily per-capita caloric consumption (Hultgren et al., 2025). By 2050, global staple crop yields are projected to be 8% lower than they would be without climate change, regardless of near-term emissions trajectories, because CO₂ already emitted will trap heat for centuries to come (Hultgren et al., 2025).

The role of producer adaptation complicates yield projections. Climate change adaptation is the alteration of current systems to reap the benefits of climate change or to minimize its harms (IPCC, 2022). Historical analyses indicate that longer growing seasons, combined with farmer adaptations, contributed to 28% of U.S. maize yield increases since 1981 (Butler et al., 2018). Conversely, adaptive strategies could reduce fractional crop losses from climate change by approximately a factor of two and could even negate losses under modest 2°C warming scenarios in the Eastern US (Butler & Huybers, 2012). At the global scale, producer adaptation and income growth are projected to alleviate approximately 34% of climate-driven losses by century's end (Hultgren et al., 2025). Yet substantial losses remain even with adaptation. Common strategies such as planting longer-maturing varieties have been insufficient to offset

heat-driven losses, and elevated CO₂ provides only weak protection against temperature-induced water stress (Lobell et al., 2013; Schauberger et al., 2017). Meeting 2050 food demands will therefore require multifaceted transformation of the food system, as no single solution is sufficient (Foley et al., 2011).

Agricultural intensification over the past half-century has altered the regional climate, further complicating the relationship between observed weather and yields. Increased irrigation, fertilizer use, and higher crop productivity have collectively enhanced evapotranspiration, cooling land surfaces, and dampening hot extremes in heavily farmed mid-latitude regions (Mueller et al., 2017). However, this cooling effect disappears during droughts in rainfed areas, where limited soil moisture prevents plants from transpiring, and the land surface anomalously heats (Mueller et al., 2016). Climate change has simultaneously increased evaporative demand and crop irrigation needs across North America, with anthropogenic forcing responsible for increased water requirements that account for approximately 11% of regional groundwater depletion since 1980 (Williams & Abatzoglou, 2025). While irrigation currently accounts for roughly 70% of global freshwater withdrawals and typically cools regional growing-season temperatures by 1–3°C, rising demand and climate change are projected to place mounting pressure on already-stressed water supplies (McDermid et al., 2023). These land-management feedbacks are large enough to partially offset locally driven greenhouse gas warming, yet they vary by region and do not reduce global warming overall (Mueller et al., 2017).

A key challenge in projecting climate-driven yield losses is correctly attributing them to their proximate causes. Temperature and soil moisture are both altered by climate change, but they interact in ways that are difficult to disentangle in statistical models. Models that use precipitation as a proxy for water availability can conflate the effects of heat and water stress

because both tend to co-occur during drought conditions. Critically, models using soil moisture rather than precipitation reduce projected damage by 28–320%, because they better separate water-supply stress from correlated heat stress (Proctor et al., 2022). This finding has direct implications for how we interpret historical relationships between climate and yield, and for how accurately we can project future losses and the benefits of irrigation as an adaptation strategy. Despite this evidence, few studies have directly leveraged paired irrigated and rainfed observations to empirically separate the effects of heat and water stress on yield.

The following analysis directly addresses this uncertainty in future yield projections by examining the contributions of heat and moisture stress to historical crop yield in U.S. maize and soybean production. This study focuses on maize and soybean, the two dominant US commodity crops, which together account for 46% of total crop cash receipts (USDA ERS, 2024). Both crops are grown extensively across the precipitation gradient of the Great Plains under both irrigated and rainfed conditions, making them ideal for disentangling the coupled effects of heat and water stress on yield. By analyzing paired irrigated and rainfed crop yield data alongside gridded climate data, we develop historical yield models to disentangle the effects of soil moisture from those of temperature. We then extend this framework to future climate projections under the IPCC's Shared Socioeconomic Pathway 2-4.5 scenario to assess how the benefits of irrigation are likely to evolve under warming conditions. Finally, we investigate the behavior of climate variables on the hottest days of the growing season to illuminate the physical mechanisms linking extreme heat to yield losses. This approach strengthens our ability to attribute historical yield trends, clarify the relative roles of heat and moisture in shaping crop outcomes, and reduce uncertainty in future yield projections under climate change.

CHAPTER 2: IRRIGATED CROP YIELDS REVEAL DISTINCT INFLUENCES OF HEAT AND MOISTURE

1 Introduction

The relationship between temperature, water availability, and crop productivity is more complex than historically assumed in many statistical yield models. The IPCC concludes with virtual certainty that the number of hot days and nights, heatwaves, and warm spells will increase in length, frequency, and intensity (Seneviratne et al., 2021). Concerns over the effects of rising temperatures have led to many studies examining crop yields under extreme daytime temperatures (Porter et al., 2014). Studies using nonlinear parameterizations determine that crop yields generally increase with temperature up to 30°C (depending on the crop type), but decline sharply beyond this threshold, with a single day at 40°C associated with a 7% reduction in maize yields compared to a day at 29°C (Schlenker & Roberts, 2009). Heat stress also disrupts the balance between photosynthesis and respiration, creating energy deficits that impair grain fill. Maize exhibits particularly high sensitivity during tasseling and silking due to the narrow temperature window required for pollen development (Butler and Huybers, 2015; Zinn et al., 2010; Prasad et al., 2008). Soybean experiences decreased pollen viability and germination, and reduced pod set under high temperatures (Djanaguiraman et al., 2013). However, the nonlinear temperature-yield relationships documented in these studies are typically interpreted as direct heat damage, without accounting for the possibility that temperature may serve as a proxy for covarying water stress.

Increasing evidence suggests that yield declines previously attributed solely to high temperatures are instead largely driven by covarying water stress rather than direct heat damage to plant physiological processes (Schauberger et al., 2017; Lesk et al., 2016). This distinction

matters because the damaging effects of extreme heat on crops strongly depend on moisture availability; extreme dry heat reduces yields substantially, while extreme humid heat has negligible or even slightly positive effects on maize and soybean production (Lesk et al., 2016). The mechanism linking heat to water stress operates through vapor pressure deficit (VPD), which accelerates evapotranspiration and depletes soil water reserves (Lobell et al., 2013). Importantly, moisture stress is not determined by water supply alone but reflects the balance between supply (precipitation, soil moisture) and atmospheric demand (temperature, VPD). Consequently, studies that account for exposure to the full range of hydroclimatic conditions outperform temperature-only models in explaining crop yield variability (Rigden et al., 2020; Choi et al., 2023). Rigden et al. (2020) found that yield damage is split almost equally between dry (53%) and waterlogged (47%) conditions, and that failing to account for soil moisture in future climate scenarios erroneously doubles the predicted yield damage attributed to atmospheric demand.

Irrigation serves both as a climate adaptation strategy and as a natural experiment for disentangling temperature effects from water stress. Adequate soil moisture enables plants to cool themselves through evapotranspiration, and irrigation reduces daytime temperatures by an average of 1.6°C during peak summer, with cooling most pronounced in hot, dry conditions (Li et al., 2020). Consistent with this mechanism, expansion of irrigation has been linked to cooling trends in extreme growing-season temperatures in heavily irrigated regions (Mueller et al., 2016). This irrigation-induced cooling effect is especially pronounced during the grain filling period of crop growth, when it appears to extend the growing season and weaken the yield response to temperature stress (Zhu & Burney, 2022). Attribution analysis of Nebraska maize suggests that water stress alleviation accounts for approximately 65% of irrigation's yield benefit,

while high-temperature stress alleviation accounts for the remaining 35% (Zhu & Burney, 2022). These proportions vary by region, reflecting differences in baseline aridity, irrigation infrastructure, and the relative intensity of heat and water stress across growing environments. Estimates based on the entire U.S. Maize Belt indicate that approximately 16% of irrigation's yield benefit in maize stems from cooling effects, and 84% from direct water supply (Li et al., 2020). In field experiments, irrigated wheat in Kansas shows no yield decline with warming, whereas rainfed wheat yields decline by 8% per 1°C increase in temperature (Tack et al., 2017). Similarly, irrigated maize in the western U.S. Maize Belt shows no significant negative impact from seasonal daytime heat, with solar radiation rather than temperature emerging as the primary yield-limiting climate variable (Carter et al., 2016). Further, yields in more irrigated counties show minimal dependency on temperature factors despite high heat exposure, while temperature-only models in non-irrigated regions are disproportionately influenced by years with extreme moisture deficits (Shaw et al., 2014).

This dynamic is particularly evident in the Great Plains, a region especially well-suited for studying the interaction between heat and water stress in crop production. The region spans a strong east-to-west precipitation gradient that supports both rainfed and irrigated agriculture within the same climatic zone, providing natural variation in water availability across otherwise similar growing conditions (Kunkel et al., 2013). Counties included in the analysis span this region, ranging from more humid rainfed systems in the east to semi-arid irrigated systems in the west, and from the distinct north-south temperature gradient from cooler northern to warmer southern growing environments (Kunkel et al., 2013). The Northern Plains states alone account for 25% of total U.S. cropland, producing approximately 26% of U.S. maize and 16% of U.S. soybean, making the region a critical component of national food security (USDA Climate Hubs,

n.d.). Irrigation in the Great Plains relies heavily on groundwater from the High Plains Aquifer, which accounts for a disproportionate share of U.S. groundwater depletion. Projections suggest that 35% of the southern High Plains will be unable to support irrigation within the next 30 years (Scanlon et al., 2012). As water availability becomes increasingly constrained, understanding the independent contributions of heat and moisture stress to crop yield losses is essential for accurately projecting agricultural damages and informing adaptation strategies.

Despite growing recognition that temperature and water stress are intrinsically linked, most statistical crop models struggle to separate these effects. High-profile analyses of climate change impacts still commonly rely upon extreme heat metrics to predict future impacts, including using nonlinear temperature specifications and accumulated degree days above certain thresholds (Hultgren et al. 2025, Ortiz-Bobea et al. 2025). Rather than relying solely on temperature metrics, we build on the well-established modeling framework of Schlenker and Roberts (2009) to examine the relative importance of heat and moisture. Here, we leverage a large dataset of paired, county-level rainfed and irrigated yield observations across the U.S. to improve our understanding of how temperature and water stress interact to affect crop yields. Using both irrigated and rainfed yield data in separate models controls for the effects of water availability and tests whether temperature-based predictors absorb the effects of water stress, thereby inflating their importance in statistical yield models. Additionally, we examine the ways heat and moisture variables covary before and after extreme heat events to illustrate the importance of moisture-related variables. Our results have important implications for the magnitude of projected yield damages and improve understanding of the agricultural consequences of climate change.

2 Methods

2.1 Historical Temperature Sensitivity Yield Modeling

Daily county-level climate data from 1981–2018 were obtained from the PRISM Climate Group, which provides spatially interpolated climate estimates derived from weather station observations at approximately 4-km resolution (PRISM Climate Group, 2024). County-level values represent spatial averages of grid cells within each county boundary. Variables included daily temperature (T_{max}/min, °C), total daily precipitation (PPT, mm), and daily vapor pressure deficit (VPD_{min}/mean/max, hPa).

Crop-specific growing seasons were defined using median emergence and harvest dates derived from USDA National Agricultural Statistics Service (NASS) Crop Progress reports for maize and soybean by state (USDA NASS, 2024). Daily climate observations were filtered to retain only dates within each growing-season window, by crop type and state. Growing-season climate variables were then aggregated annually by county: temperature and VPD were averaged, and precipitation was summed. Only counties with at least 10 years of observations were retained for analysis to ensure sufficient temporal coverage for trend detection.

Killing Degree Days (KDD) and Growing Degree Days (GDD) were calculated using a diurnal temperature profile approach following established methodologies (Campbell & Norman, 1998). Hourly temperatures were estimated from daily T_{max} and T_{min} using a sinusoidal weighting function that accounts for typical diurnal temperature variation. For KDD, hourly temperatures exceeding a 30°C threshold were summed and divided by 24 to calculate daily KDD values (Schlenker & Roberts, 2009). For GDD, hourly temperatures were bounded by a 10°C base and 30°C cap before calculating degree-day accumulation following established thresholds (Gilmore & Rogers, 1958; Major et al., 1975). Daily KDD and GDD values were

summed across each county's growing season to produce annual heat-stress (annual KDD) and moderate-temperature thermal-accumulation (annual GDD) metrics ($^{\circ}\text{C}\cdot\text{day}$).

County-level yield data for maize (grain only) and soybean were obtained from USDA NASS (USDA NASS, 2022) for counties that reported yields (bu/ac) separately for irrigated and rainfed production systems. The paired nature of this dataset is central to our analytical approach. By retaining only counties that report both irrigated and rainfed yields in the same year, we can directly compare how temperature and water stress affect yields under contrasting water availability conditions within the same location and time period. This within-county pairing effectively controls for confounding factors such as soil type, management practices, and local climate. Because heat and water stress are correlated in agricultural landscapes, temperature-only models may conflate the effects of moisture deficits with heat stress. Retaining only counties with both irrigated and rainfed observations provides a within-location contrast in water availability, allowing the effects of temperature and water stress to be estimated more independently. After applying a minimum 10-year paired data requirement to ensure sufficient temporal coverage, the final dataset included 305 counties spanning 10 states, predominantly in the Great Plains agricultural region (Kansas, Nebraska, North Dakota, South Dakota, Arkansas, and Colorado). Figure 1 shows the spatial distribution of included counties and the number of years of paired observations available per county.

A linear regression model was specified separately for each crop (maize and soybean) and water regime (irrigated and rainfed) to estimate yield responses to heat stress while controlling for technological trends and spatial heterogeneity (Equation (1)). Where γ_c represents county fixed effects capturing county-level heterogeneity, θ_γ represents year fixed effects

controlling for temporal shocks, and ε_{cy} is the error term. Model performance was evaluated using adjusted R^2 , AIC, and BIC.

$$Yield_{cy} = \beta_1 KDD_{cy} + \beta_2 GDD_{cy} + \beta_3 PPT_{cy} + \beta_4 PPT^2 + \gamma_c + \theta_y + \varepsilon_{cy}$$

Equation (1)

To account for spatial and temporal correlations, a state-year block bootstrap procedure with 1,000 iterations was implemented to quantify uncertainty. For each bootstrap iteration, state-year blocks were randomly resampled with replacement to construct a dataset of the same size as the original. The regression model was re-estimated on each bootstrap sample, and coefficient distributions were compiled across all iterations. Point estimates were reported as the mean of the bootstrap distribution, and 95% confidence intervals were reported as the 2.5th and 97.5th percentiles for the KDD coefficient (β_1). This resampling strategy provides robust uncertainty estimates that account for two-way clustering at both the state and year levels, which is critical for panel data spanning multiple jurisdictions and time periods.

2.2 Climate Projections and Future Yield Estimates

Future climate data were obtained from the Multivariate Adaptive Constructed Analogs (MACA) dataset (Abatzoglou & Brown, 2012) using five Global Climate Models (GCMs) under the SSP2-4.5 emissions scenario: GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL. The same daily climate variables taken from the historical data were extracted from bias-corrected CMIP6 projections for all counties included in the historical training dataset (305 counties across 10 states) for the period 2015–2100.

Daily KDD and GDD values were calculated from projected temperatures using the same diurnal temperature weighting approach applied to historical data. Climate variables were

aggregated to the annual growing season: GDD and KDD were summed, precipitation was totaled, and VPD was averaged across each state-crop growing season and county.

Predictions were generated separately for each crop (maize and soybean), water regime (irrigated and rainfed), and GCM. For each combination, annual county-level yields were predicted from 2015 to 2100 using the fitted regression coefficients and projected climate inputs for all counties present in the historical training data. The year variable in all regression models was held constant at 2018 (the final year of the historical training period), while future climate conditions (KDD, GDD, PPT, VPD) varied according to GCM projections. This approach does not attempt to project future technological growth, allowing predictions to reflect isolated climate impacts. To summarize projection uncertainty across GCMs, the mean, minimum, and maximum predicted yields for each county, year, and water regime were calculated.

2.3 Anomalies Associated with KDD Accumulation

To characterize the hydroclimatic conditions surrounding extreme heat events, daily anomaly composites were constructed around days of KDD accumulation. Daily historical climate data were obtained from the PRISM dataset, providing gridded estimates of maximum temperature (Tmax), minimum temperature (Tmin), precipitation (PPT), and maximum vapor pressure deficit (VPDmax) at the county level. Daily soil moisture (m^3/m^3) was additionally derived from the NASA Land Data Assimilation System (LDAS; Jasinski et al., 2019) for three depth intervals: 0–10 cm, 10–40 cm, and 40–100 cm. County-level FIPS codes were used to spatially match all climate and soil moisture records, and the dataset was subset to counties present in the crop yield records. All variables were processed and merged into a single daily dataset spanning 1981–2018.

Daily anomalies for each variable were calculated relative to a day-of-year (DOY) climatological mean computed independently for each county. For each county and calendar day, the climatological mean was calculated by averaging observed daily values across all years in the record. To reduce residual day-to-day sampling noise, a centered 15-day moving average (± 7 days) was applied to the DOY climatology prior to computing anomalies. Daily anomalies were then defined as the difference between the observed daily value and the smoothed climatological mean for the corresponding DOY and county.

To understand climate and soil moisture patterns associated with KDD accumulation, hot days were defined as those with a maximum temperature exceeding 30°C. For each hot day, anomalies for each variable were extracted over a 61-day window centered on the hot day (± 30 -days). Anomalies were weighted by the KDDs accumulated on each hot day, so that days with greater heat stress contributed proportionally more to the composite signal. A state-year block bootstrap was performed by resampling state-year combinations with replacement 1,000 times and calculating the weighted mean anomaly response for each iteration. The 2.5th and 97.5th percentiles of the resampled means were used to construct 95% confidence intervals.

3 Results

3.1 Decoupling Heat and Soil Moisture Influence on Historical Yields

Results from the linear regression models relating climate variables to yield are shown in Table 1. Results from the KDD coefficient alone are shown in Figure 2. Models were fit separately for each crop and irrigation type. For rainfed soybean, cumulative annual killing degree days (KDDs) were negatively associated with yield ($p < 0.001$), while irrigated soybean showed no significant KDD effect ($p > 0.05$), indicating that irrigation effectively eliminated heat stress impacts. Similarly, for both irrigated and rainfed maize, cumulative annual KDDs were

negatively associated with yield; rainfed maize was 2.4x more sensitive to KDDs than irrigated maize. Maize exhibited larger negative KDD coefficients than soybean, indicating greater sensitivity of maize yield to heat stress under both water regimes. Notably, precipitation and precipitation² were not significant predictors of yield in irrigated systems for either crop, whereas in rainfed systems, precipitation terms were significant for both maize and soybean. This is expected, as irrigated systems are largely decoupled from natural precipitation, making precipitation a poor predictor of yield variability under irrigation.

3.2 Decoupling Heat and Soil Moisture Influence on Future Yield Projections

Future maize and soybean yields were projected using the historically parameterized regression models to evaluate irrigated and rainfed system responses to climate change. Figure 3 shows the estimated average yields for both crops and water regimes from 2015 to 2100. Both maize and soybean exhibit declining yield trends over time, with notable fluctuations likely due to interannual variability in climate. Rainfed systems experienced larger reductions than irrigated systems for both crops. Maize yields decline by 14% under irrigation and 50% under rainfed conditions from 2015 to 2100, reflecting strong sensitivity to water availability. Soybean yields are lower overall, with irrigated yields declining modestly by 9% and rainfed yields dropping sharply by 75%, suggesting that, under current technology and management, projected climate change alone could dramatically reduce rainfed soybean productivity by the end of the century. These results indicate that irrigation mitigates the negative effects of projected climate change for both crops, particularly for maize. Rainfed soybean yields, however, still experience large proportional reductions despite smaller absolute reductions under irrigation.

3.3 Examining KDD Accumulation's Effect on Climate Variables

To better understand the dynamics of climate variables around extreme heat accumulation (i.e., KDDs), anomaly plots are used to visualize the average dynamics of soil moisture, precipitation, and VPD before, during, and after the average KDD accumulation. Figure 4 displays the KDD-weighted average anomalies of precipitation, soil moisture at 0–10 cm, 10–40 cm, and 40–100 cm depths, maximum, minimum, and mean VPD, and maximum temperature over a 61-day window during KDD accumulation events. All variables exhibit pronounced deviations from their mean state near the hot day. VPD anomalies peak on hot days, suggesting that extreme heat events are characterized by high evaporative demand for water. Precipitation deficits emerge roughly 10 days prior, consistent with drier antecedent soils reducing latent heat flux and increasing sensible heat flux at the land surface, which amplifies near-surface air temperatures (Seneviratne et al., 2010). The precipitation deficit peaks the day before the hot day, reflecting the tendency for extreme heat events in the U.S. to be broken by convective storms. Soil moisture deficits are present throughout the soil profile, peaking on the hot day across all depths, with larger deficits near the surface (0–10cm) that attenuate with depth. Following the hot day, soil moisture deficits persist for weeks, with negative anomalies continuing well beyond the event itself in the deeper profiles. Notably, KDD accumulation is associated with a prolonged period of both elevated water demand and decreased water supply occurring roughly ± 10 days around the KDD accumulation.

4 Discussion

4.1 Heat and Moisture Stress Are Coupled

Historical anomaly analysis surrounding extremely hot days reveals that heat events do not occur in isolation but are accompanied by lower precipitation, depleted soil moisture across

all depths, and elevated VPD (Figure 4). This coupling creates compounded stress conditions that confound the attribution of yield losses to heat versus water stress in traditional statistical models. The challenge in separating these effects arises because extreme heat accumulation is typically associated with prolonged dry conditions, making it difficult to determine whether observed yield declines result from direct physiological heat damage or from temperature-induced water stress.

4.2 Paired Irrigated and Rainfed Yields Isolate Heat Effects

The unique dataset of paired rainfed and irrigated crop yields allows us to better control for soil moisture effects, though imperfectly, since farmers do not irrigate optimally and irrigated crops can still experience water stress (U.S. Government Accountability Office, 2020). By comparing yield responses to KDDs across water regimes, we isolate the portion of yield loss attributable to heat alone from that mediated by water availability (Figure 2). The results demonstrate that the associations between heat and moisture account for a large portion of the yield signal typically attributed to extreme heat. Linear regression results show that KDD has a substantially larger negative coefficient in rainfed systems than in irrigated systems for both crops (Table 1, Figure 2). For maize, the KDD coefficient is reduced from -0.831 in rainfed systems to -0.346 under irrigation, a 2.4-fold reduction. For soybean, the effect is even more dramatic: the KDD coefficient drops from -0.194 in rainfed systems to a statistically insignificant -0.002 under irrigation, indicating that heat stress effects are almost entirely water-mediated for this crop.

4.3 Crop-Specific Patterns in Heat Sensitivity

While maize exhibits larger absolute KDD coefficients than soybean, this difference partly reflects maize's higher baseline yields, which naturally produce larger coefficient

magnitudes. When examined proportionally, soybean shows a greater relative difference between rainfed and irrigated systems, with irrigated soybean yields showing no significant response to extreme heat. This pattern suggests that soybean yield's apparent heat sensitivity in rainfed systems is driven almost entirely by water stress, whereas maize retains some direct physiological sensitivity to high temperatures even when adequately irrigated. The observed negative effects of KDD on yield in rainfed systems reflect the physiological impacts of heat stress, including reduced photosynthetic efficiency, accelerated reproductive development, and increased respiration in both crops. Maize, with its high sensitivity during tasseling and silking, is especially vulnerable to heat-induced kernel abortion (Butler & Huybers, 2015; Prasad et al., 2008). Soybean experiences reductions in pod set and seed size under high temperatures, but these effects are largely eliminated when water availability is maintained through irrigation (Djanaguiraman et al., 2013).

4.4 Future Yield Projections Under Climate Change

Projected yields from 2015 to 2100 under SSP2-4.5 suggest that rainfed systems will experience severe declines, with maize dropping from 87 to 44 bu/acre (50% decline) and soybean from 19 to 5 bu/acre (75% decline), while irrigated systems show more moderate reductions of 14% for maize and 9% for soybean (Figure 3). These diverging trajectories underscore that water availability, rather than heat per se, is the primary determinant of future yield losses under climate change. These results have several implications for climate adaptation policy and future research. The divergence between future irrigated and rainfed yield trajectories underscores the importance of water access for agricultural resilience, suggesting that policies to maintain sustainable irrigation infrastructure will be critical for buffering food production against climate change. However, the long-term viability of irrigation in the Great Plains, as well as the

whole U.S., is constrained by groundwater depletion (Scanlon et al., 2012). Future research should examine how heat-tolerant or drought-resistant varieties, optimized planting dates, and precision irrigation practices interact with the coupled heat-moisture stress dynamics identified here, as these interventions may reduce vulnerability in both irrigated and rainfed regimes.

5 Conclusions

This study demonstrates that the negative effects of extreme heat on maize and soybean yields are substantially mediated by water availability, with temperature-based predictors such as KDDs absorbing much of the water-stress signal in rainfed systems. Using paired rainfed and irrigated yield observations across the U.S., we found that KDD coefficients are dramatically reduced under irrigation: maize showed a 2.4-fold reduction (from -0.831 to -0.346), and soybean showed complete elimination of heat-stress effects (from -0.194 to a statistically insignificant -0.002). What appears as heat damage in statistical models of rainfed systems largely reflects temperature-induced water stress rather than direct physiological heat damage. Anomaly analysis confirms that extreme heat events coincide with reduced precipitation, prolonged soil moisture deficits, and elevated VPD, creating compounded stress conditions that disproportionately impact rainfed crops. Projections through 2100 under SSP2-4.5 reveal substantial yield declines in rainfed systems (50% for maize, 75% for soybean) while irrigated systems show relatively modest losses (14% for maize, 9% for soybean), highlighting irrigation's critical role in buffering yields against losses from future climate change. Future research should explicitly model the interaction between temperature extremes and soil moisture availability to improve yield projections and inform climate adaptation planning. These findings contribute to a growing body of evidence that the agricultural consequences of climate change are deeply intertwined with water availability, and that improving the accuracy of yield damage projections

requires moving beyond temperature-only frameworks toward models that explicitly account for the coupled dynamics of heat and moisture stress. As climate change intensifies heat extremes and evaporative demand, maintaining sustainable irrigation practices will be essential for global food security.

All analysis for this chapter was completed using RStudio Version 2024.04.2+764. The data and code required to reproduce the figures and analyses are available by request.

CHAPTER 3: CONCLUSIONS

This study provides evidence that the sensitivity of maize and soybean yields to extreme heat in statistical crop models is largely driven by temperature-induced water stress rather than by direct physiological heat damage. Using historical paired rainfed and irrigated yield observations across the U.S., we found that KDD coefficients are substantially lower under irrigation. Anomaly analysis reinforces this interpretation, confirming that extreme heat events occur with reduced precipitation, depleted soil moisture across all depths, and elevated VPD. These findings directly support and extend prior work by Proctor et al. (2022), who showed that models using soil moisture rather than precipitation reduce projected yield losses by better separating water stress from correlated heat stress. With our paired irrigated–rainfed approach, we isolate the temperature signal that remains when crops are not also water-stressed.

Chapter 1 established that the global food system faces a convergence of accelerating climate pressures and rapidly growing demand, and that the scientific literature has increasingly attributed yield losses to high temperatures that conflate heat and water stress. The analysis presented in Chapter 2 directly addresses this ambiguity. By projecting the divergence in irrigated and rainfed yields through 2100 under SSP2-4.5, we see that irrigation is not merely a short-term strategy but a critical long-term buffer against climate-driven yield losses. At the same time, these projections reinforce the warning from Chapter 1 that irrigation is under mounting pressure, with rising evaporative demand and groundwater depletion threatening the irrigation that will provide this buffer (Williams & Abatzoglou, 2025; McDermid et al., 2023).

Several limitations are present in this analysis. First, the paired irrigated–rainfed design assumes that the primary difference between the two systems is water availability, but irrigated and rainfed fields may also differ in management intensity and crop variety selection, which are not fully captured by available data. Second, both USDA yield statistics and our aggregated weather data are at the county-level, potentially obscuring systematic patterns in the distribution of rainfed and irrigated areas. For example, irrigated fields may be systematically located in lower-lying areas near rivers or water sources, meaning irrigated and rainfed fields within the same county may experience meaningfully different microclimates and growing conditions beyond just water availability. This spatial confounding could bias coefficient estimates if the climate conditions experienced by irrigated fields differ systematically from those of rainfed fields. Third, while SSP 2-4.5 represents an intermediate emissions trajectory, it is not a given future, and other SSP scenarios may be considered more likely. Fourth, this analysis does not account for potential CO₂ fertilization effects or farmer adaptation responses such as varietal switching and shifts in planting dates, both of which could partially offset projected losses. Finally, the framework is modeled on historical climate–yield relationships that may not fully capture all yield determinants. Future work should explicitly model the interaction between temperature and soil moisture in both statistical and process-based crop models, extend this paired framework to global datasets, and test projections across a range of SSP scenarios to better compare uncertainty in future outcomes.

The central contribution of this work is an empirical analysis of heat and water stress in agricultural yield models, leveraging collocated irrigated and rainfed fields. By demonstrating that what appears as heat damage in rainfed statistical models is largely determined by water stress, this study has direct implications for projections of agricultural damage. Models that do

not account for the coupled nature of temperature and water availability will overestimate the direct effects of rising temperatures while underestimating the value of water management as an adaptation strategy. As climate change simultaneously intensifies heat extremes and increases evaporative demand, this distinction becomes increasingly consequential for policy. Securing future global food production will require not only investment in irrigation infrastructure but also a more accurate accounting of where yield losses originate.

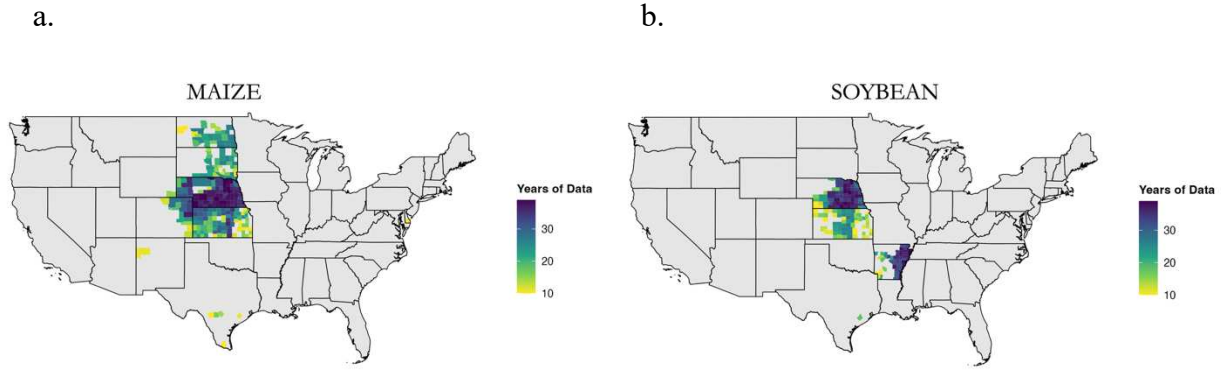


Figure 1. County-level data availability for (a) maize and (b) soybean yields across the contiguous U.S. Color indicates the number of years of paired irrigated and rainfed yield observations available per county, with darker shades representing more years and lighter shades fewer. Only counties with at least 10 years of observations are included.

Table 1. County-level linear regression results for maize and soybean under irrigated and rainfed production, including coefficients for annual KDD ($^{\circ}\text{C}\cdot\text{day}$), annual GDD ($^{\circ}\text{C}\cdot\text{day}$), precipitation (cm), and precipitation squared (cm^2), along with 95% confidence intervals, number of observations, and R-squared values. County and year fixed effects were included, and confidence intervals were obtained using a state-year block bootstrap with 1000 replications. County factor variables were included in the models but are not reported in the table. * $p<0.05$, ** $p<0.01$, *** $p<0.001$

Maize — Irrigated		
Predictor	Estimate	95% CI
Killing Degree Days	-0.346***	[-0.431, -0.207]
Growing Degree Days	0.069*	[0.05, 0.08]
Precipitation	-0.038	[-0.458, 0.383]
Precipitation ²	-0.003	[-0.007, 0.001]
Observations	6689	
R-squared	0.714	
Maize — Rainfed		
Predictor	Estimate	95% CI
Killing Degree Days	-0.831***	[-1.05, -0.71]
Growing Degree Days	0.067**	[0.055, 0.089]
Precipitation	1.568***	[1.068, 2.126]
Precipitation ²	-0.011*	[-0.016, -0.005]
Observations	6689	
R-squared	0.726	
Soybean — Irrigated		
Predictor	Estimate	95% CI
Killing Degree Days	-0.002	[-0.032, 0.035]
Growing Degree Days	-0.02*	[-0.023, -0.017]
Precipitation	0.132	[-0.028, 0.276]
Precipitation ²	-0.001	[-0.003, 0.001]
Observations	4502	
R-squared	0.760	
Soybean — Rainfed		
Predictor	Estimate	95% CI
Killing Degree Days	-0.194***	[-0.239, -0.144]
Growing Degree Days	-0.006*	[-0.01, -0.001]
Precipitation	0.627***	[0.404, 0.806]
Precipitation ²	-0.006*	[-0.007, -0.003]
Observations	4502	
R-squared	0.748	

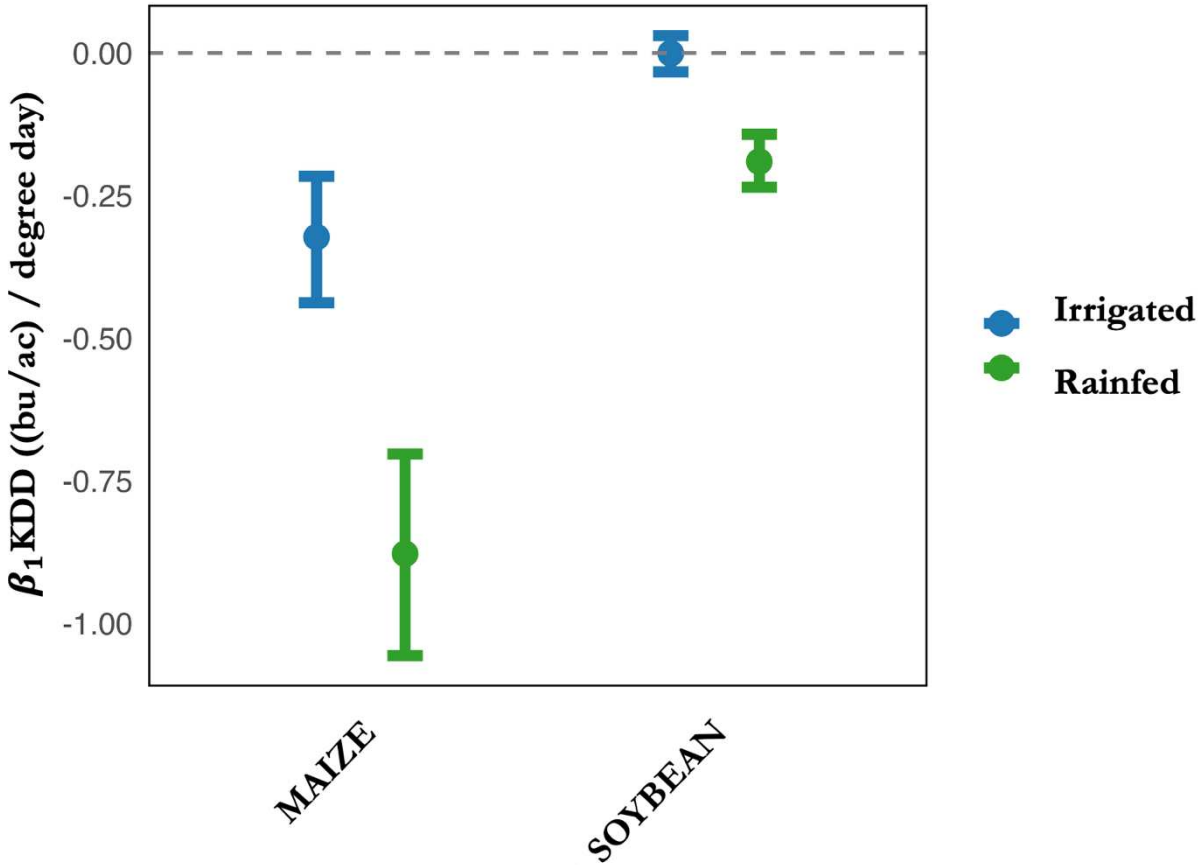
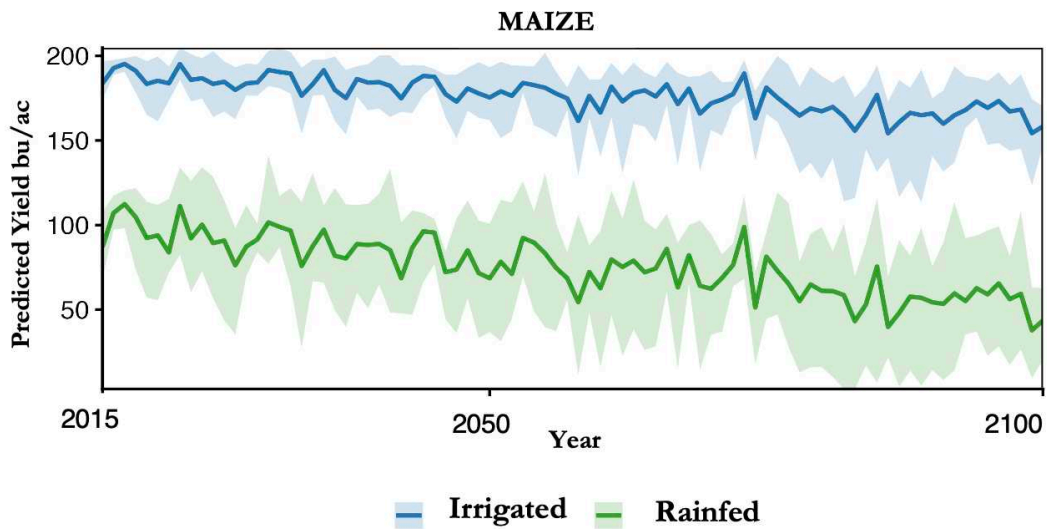


Figure 2. Estimated coefficients for cumulative annual Killing Degree Days (KDD) from county-level linear regression models for maize and soybean yields under irrigated and rainfed conditions. Circles indicate coefficient estimates, and bars show 95% confidence intervals obtained via state-year block bootstrapping. Blue symbols represent irrigated yields, and green symbols represent rainfed yields. Maize estimates are shown on the left, and soybean estimates on the right.

a.



b.

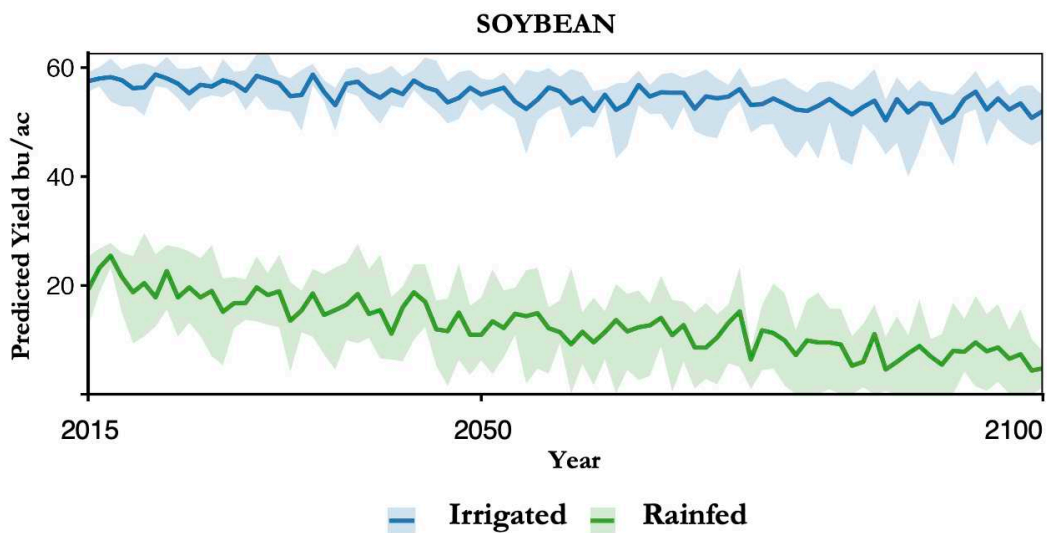


Figure 3. Projected (a) maize and (b) soybean yield from 2015 to 2100 under irrigated and rainfed conditions across five Global Climate Models (GFDL, IPSL, MPI, MRI, UKESM) for SSP2-4.5. Solid lines show the mean GCM-specific average yields across all counties, and shaded areas indicate the minimum and maximum yields across the models. Blue lines represent irrigated yields, and green lines represent rainfed yields. Note: 2015–present shows plausible projected yields, not observed values.

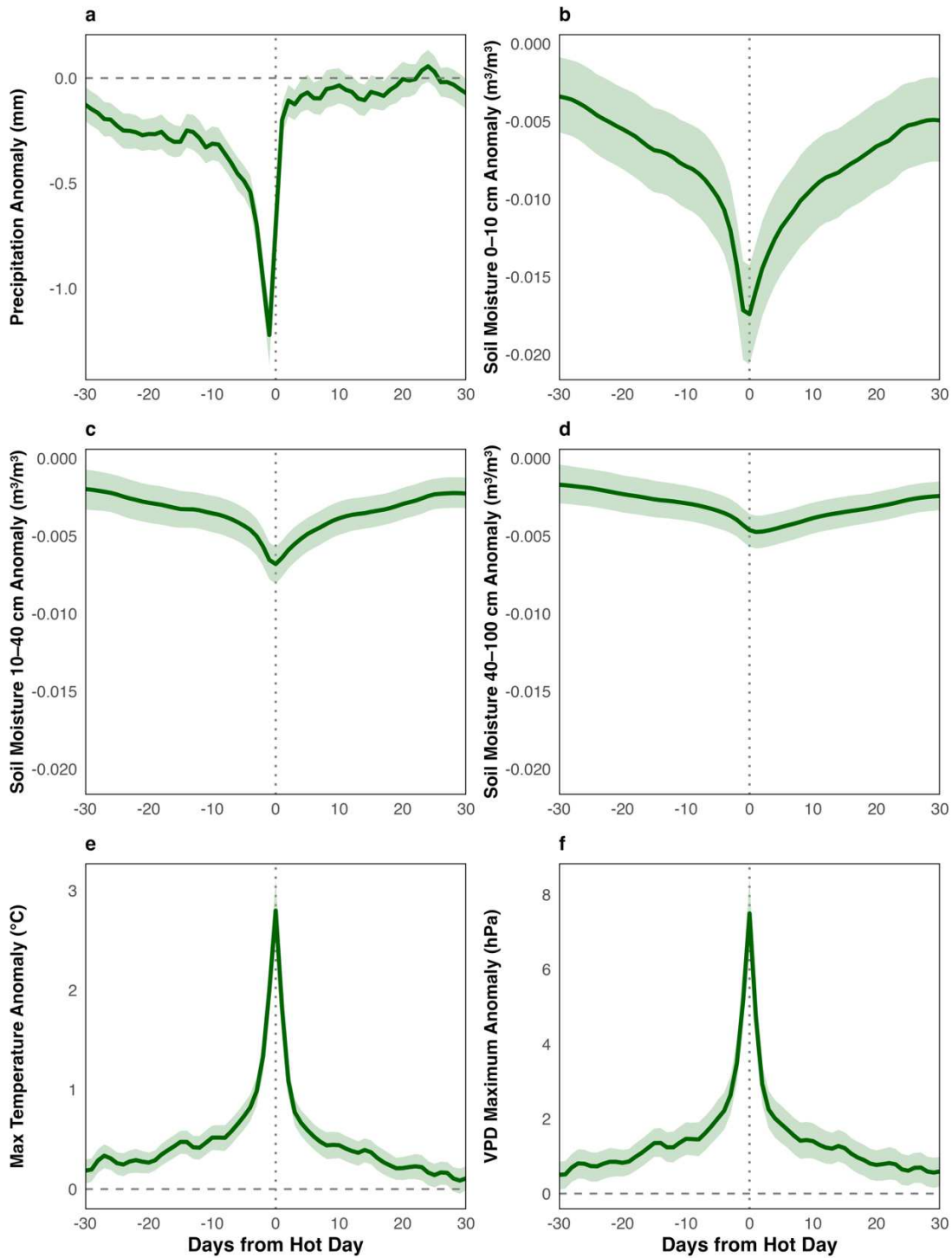


Figure 4. Historical anomalies of climate variables surrounding extreme heat events (days $\geq 30^{\circ}\text{C}$), weighted by daily Killing Degree Days (KDD). Panels show (a) precipitation, (b) soil moisture at 0–10 cm, (c) soil moisture at 10–40 cm, (d) soil moisture at 40–100 cm, (e) maximum temperature, and (f) maximum vapor pressure deficit (VPD). Anomalies are calculated over a 61-day window centered on the heat event (day 0), with shaded bands representing 95% confidence intervals from a state-year block bootstrap ($n = 1,000$ iterations).

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