Diversified crop rotations mitigate agricultural losses from dry weather

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Abstract

As changing climates create drought conditions with increasing frequency and severity, there is an urgent need for farmers to adopt agricultural systems that lower the risk of losses during drought. Diverse crop rotations have long been associated with a wide array of economic and environmental benefits, yet cropping systems in the US Midwest and across the world have been simplifying for over a century. Long-term experiments have shown potential for diverse rotations to avoid yield losses under dry conditions, and could be an impactful target in a region overwhelmingly dominated by corn-soy rotation. Here we use Bayesian modeling to show spatial patterns of yield benefits that result from increasing rotational diversity in a range of weather conditions. Data from over 2.2 million field-years reveal that diverse rotations decrease the risk of corn yield losses in dry years in areas that experience these conditions more frequently, while simultaneously increasing yields under favorable conditions across the region. The potential for yield risk mitigation described in the current analysis underscores the critical need for crop rotation adoption as changing climates threaten yield stability in the US and across the globe. We highlight areas where diverse rotations are most likely to improve yields and mitigate risk, amidst spatial heterogeneity in the magnitude of these benefits.

Significance

Dry weather can be devastating to agricultural systems. The 2012 drought in the US Midwest cost $17.4B in crop insurance indemnity payments, while global droughts cause enormous strains on food production and farm economies. Tools that can accurately assess agricultural risk alongside the benefits of changes in management practices are urgently needed to finance climate resilient transformations of food systems. Shifting policies can then pass this value to farmers who use more diversified cropping systems and encourage their adoption in areas where it is most likely to benefit farmers.

1. Introduction

Farming has always been risky, with droughts, floods, heat waves and other hazards harming crop production and farmers' livelihoods for millenia across the world. Climate change increases the severity and frequency of these hazards (Hao et al., 2018; USGCRP, 2018). Heavier spring rainfall and drier summers are already disrupting agriculture in the U.S. Midwest (Swain and Hayhoe, 2015; Feng et al., 2016), one of the most intensively farmed regions in the world (Ramankutty and Foley, 1998). For example, the 2012 drought in the U.S. Midwest reduced corn (*Zea mays*) yields by ~25% (Boyer et al., 2013), causing what was then the U.S. government's most expensive year for crop insurance payouts at $17.4 billion. This figure was topped again in 2022 when payouts soared to a record $19.1B amidst drought, flooding, and heat waves (Schechinger, 2023a, 2023b). In 2019, historic spring flooding coupled with summer drought combined to cause a 20% spike in farm bankruptcies over the prior year (Newton, 2020). While safety nets like crop insurance help mitigate farmers' revenue risk, they do not protect agricultural production from being disrupted, with concomitant price spikes in food and other sectors. To avoid these outcomes, as well as large increases in subsidies for public safety nets, it is critical for many agricultural systems around the world to become more resilient to a changing climate.

Like other regions, farming in the past century in the U.S. has relied heavily on monoculture or limited crop rotation (Bullock, 1992; Plourde et al., 2013), reducing the frequency of diverse rotations that include multiple species in their sequence of harvested crops. In the Midwest, specialization in just two crops, corn and soybeans, have made the region vulnerable to stressful weather events (Ortiz-Bobea et al., 2018). Crop rotational diversity stabilizes yields at farm and regional scales via the "portfolio effect" (Renard and Tilman, 2019), as well as via positive feedbacks to soil and other agroecosystem components. Agricultural simplification has suppressed the benefits of diverse rotations, which can enhance soil health (Ball et al., 2005), reduce pest pressures (Brust and King, 1994), and increase soil nitrogen availability (Sindelar et al., 2016).

Several recent syntheses of long-term agricultural experiments show that diversified crop rotations can reduce the risk of weather-related yield declines. For example, more diverse rotations reduced corn yield losses by 14–90% in drought years in half of the 11 long-term experiments spanning a continental precipitation gradient in the U.S. and Canada (Bowles et al., 2020). In seven long-term experiments in Europe, winter and spring cereal yield gains in diverse rotations were up to 1000 kg ha^{-1} higher than monoculture in years with high temperature and little precipitation (Marini et al., 2020). Sanford et al. (2021) showed that as the number of crops in rotation increases, yield declines diminish during drought. However, all these results are based on plot-level studies from research stations, which do not always translate into field-scale results on working farms (Kravchenko et al., 2017).

A gap therefore remains in understanding how diversified systems perform at a commercial, field-scale level, especially under the varying conditions experienced on working farms. Our study aims to bridge this gap by providing concrete evidence of the benefits of diverse rotations and their variation at a fine scale across a wide region. Climate conditions, intrinsic soil properties, regional management trends, and other factors modulate the extent to which crop rotation promotes resilience of specific crops to specific stressors (Beal Cohen et al., 2019; Kluger et al., 2022). These factors may interact in complex ways, requiring yield data across widely varying conditions to build statistical models that can sort out yield responses to real-world conditions. Thus, an additional and major knowledge gap exists in identifying spatial patterns of risk mitigation from rotational diversification.

Economic incentives in the current U.S. federal crop insurance system may actually encourage simplified crop rotations (Yu et al., 2018). If diversified cropping systems do reduce production and/or profitability risks, then the dollar value of this risk reduction could be applied to insurance and lending policies and passed onto farmers. But passing on these savings will require an actuarially sound, quantitative understanding of the risk reduction associated with these practices. Though prior work has leveraged such large, field-scale datasets to better understand management outcomes and practice adoption (Seifert et al., 2018; Socolar et al., 2021), to this point no work has examined how diversified cropping systems affect the full probability distribution of crop yields in different growing conditions. These complete distributions can allow for calculation of risks and opportunities that vary over time and space, and during stressful weather events. Estimating the probabilities of unlikely extremes, not just mean responses, is essential for accurately gauging the effects of cropping systems on risks and opportunities. Computations for probabilities of these tail events can help describe the true benefit of alternative cropping systems in managing risk.

In this study, we used data from all of the nearly 400,000 fields implementing corn-based rotations in two contrasting states in the U.S. Corn Belt to determine the spatial patterns and magnitudes of crop rotation diversification's impacts on rainfed corn yields during stressful weather. We hypothesized that diversified rotations would be associated with reduced corn yield losses during dry weather without substantial opportunity costs during favorable weather. Using remotely-sensed estimates of crop yields and rotational complexity, we conducted Bayesian statistical modeling focused on corn responses to summer dry periods under varying levels of rotational complexity (Figure 1). We used data from over 2.2 million field-years, constructing spatially variable county-level models to account for changes in yield's response to environmental predictors across space. We quantified yield responses to adopting diversified rotations, asking whether more complex rotations mitigate the probability of crop yield losses as weather becomes hotter and drier, and whether trade-offs exist between benefits in suboptimal conditions and crop performance under favorable conditions. We found that diverse crop rotations protect against losses in drier years in Illinois but not Minnesota, without changing outcomes in typical years, providing a basis for valuing risk mitigation ecosystem services of complex rotations in actuarial and financial contexts. With climate change expected to increase the frequency and severity of droughts in critical grain producing regions, our results point toward rotational complexity as an important agricultural climate adaptation strategy and highlight the actuarial benefits of transitions to more diversified cropping systems in the US Midwest, as well as the promise of applying these analyses in other regions across the US and globe.

2. Methods

2.1 Study Area

Analysis focused on two states, Illinois and Minnesota, which are both part of the "Corn Belt" region in the Midwestern United States. Corn dominates the landscape in the Midwest, with over half of its cropland planted in corn-soy rotations or corn monoculture every year, resulting in an annual corn acreage the size of Norway (USDA/NASS, 2017). The selection of Illinois and Minnesota as our primary study areas was driven by their prominent roles in U.S. corn production and the contrasting climatic and agricultural practices observed between these states. Illinois and Minnesota were both among the top five corn producers in the country for the entirety of the 2006-2020 study period (USDA/NASS, 2023). While both top corn producers, the two states contrast one another in both climate and crop rotation practices. For example, in the past two decades Minnesota has experienced fewer dry periods that significantly impact crop production than Illinois, and shows a higher average complexity in corn rotations (Socolar et al., 2021).

2.2 Data Sources

This study involved processing and aggregating field-level data from a variety of sources (Table S1) to understand the relationships between corn yield, rotational complexity, soil characteristics, and weather.

2.2.1 Yield. Since farmer-reported field-level corn yield data are not publicly available, we used corn yield maps derived from the Scalable Crop Yield Mapper (SCYM) (Lobell et al., 2015; Jin et al., 2017). SCYM was chosen for yield data estimation due to its high accuracy and extensive validation at both field and county scales (Jin et al., 2017; Deines et al., 2021). See supplement for details on SCYM performance. As SCYM results are reported in terms of total aboveground biomass, we assume a harvest index of 0.5 when reporting yields (Deines et al., 2021; Ruiz et al., 2023).

2.2.2 Rotational Complexity Index (RCI). RCI allows quantitative comparisons of rotational diversity on farm fields, offering a continuous scale of comparison that encompasses the entire region, rather than limiting analysis to a small number of representative rotations (Socolar et al., 2021). We calculated RCI for all fields in all years with at least six years of USDA Cropland Data Layer (CDL) history (the focal year in addition to the five previous) (Boryan et al., 2011). RCI was calculated according to the methods detailed in Socolar et. al., 2021. In brief, an index ranging from 0 (monoculture corn for six years) to 5.2 (a different crop grown each year) was calculated for each field in each year based on the number of crop species and frequency of crop turnover in its immediate six-year history. RCI was calculated based on field-level crop histories representing the mode crop across CDL pixels for each field in each year.

2.2.3 National Commodity Crop Productivity Index (NCCPI). We used NCCPI (Dobos et al., 2012) as a proxy for land quality (Seifert et al., 2018; Socolar et al., 2021). The highest value from the NCCPI submodels (corn/soy, cotton, and small grains) was used for each pixel (30x30m). NCCPI ranges from 0 to 1 with higher values corresponding to greater soil productivity.

2.2.4 Vapor pressure deficit (VPD). We used VPD–which increases with hot, dry conditions– as the indicator of corn water stress and agricultural drought, in line with prior studies (Lobell et al., 2014). Vapor pressure deficit is mechanistically linked with corn stomatal regulation and the intensity of water stress (Kimm et al., 2020), and corn yield has a strong negative association with increasing July maximum VPD above a threshold value of ~20 hPa (Xu et al., 2021). We included monthly maximum VPD during the May-August growing season in our exploratory data analysis, and ultimately included Maximum July VPD as a model predictor (Figure S1).

2.2.5 Field boundaries. Corn yields, CDL, and NCCPI were extracted and aggregated to the field level according to remotely sensed field boundaries (Yan and Roy, 2016). Field-level time series were constructed by computing the arithmetic mean of values of all grid points that fall within the boundary of each field for each variable, or mode field value in the case of the CDL.

2.3 Inclusion criteria

To ensure sufficient modeling sample sizes, predictor variation, and scale of downside and upside probabilities, we imposed various restrictions on our modeling and prediction (see “County inclusion Criteria” in supplement). In short, our inclusion criteria, particularly the minimum sample size for a county and the threshold for July maximum VPD, were chosen to avoid overfitting or unreliable conclusions from counties with sparse data. The July maximum VPD threshold was set based on previous research indicating a linear relationship between VPD levels (20-40 hPa) and corn yield impact, with VPD having little impact on yield below this threshold. This selective approach allowed us to focus on conditions where VPD is most likely to affect yields, thus providing a more accurate understanding of the relationship between weather stress, rotational complexity, and corn yield. Our inclusion criteria left 124 of 189 total counties in our analysis (Figure 2).

2.4 Bayesian Mixed Effects Model and spatial considerations

The Bayesian framework provides a principled way of accounting honestly for model, parameter, and measurement uncertainty quantification. Bayesian analysis accounts for uncertainty at all levels, with predictions that typically exceed the predictive power of classical frequentist analysis, particularly in observational studies like ours (see (Dunson, 2001) for general arguments, and (Prost et al., 2008) for the case of yield gaps).

For each of 124 counties in Illinois and Minnesota, we fit a Bayesian mixed effects model to characterize the relationship between field-level yield and crop rotational complexity as defined in the following equation:

$$
\begin{gathered}
yield_{i,t} = \beta_0 + \beta_1 RCI_{(m)i} + \beta_2 RCI_{(w)i,t} + \beta_3 VPD_{i,t} + \beta_4 NCCPI_i \\
+ \beta_5 VPD_{i,t} RCI_{(m)i} + \beta_6 VPD_{i,t} RCI_{(w)i,\,t} \\
+ \beta_5 NCCPI_i RCI_{(m)i} + \beta_8 year_t + \alpha_i + \epsilon_{i,t} \\
\alpha_i \sim N(0,\ \sigma_\alpha^{\ 2}) \\
\epsilon_{i,t} \sim N(0,\ \sigma_\epsilon^{\ 2})
\end{gathered}
$$

where yields at field i in year t are modeled as a linear combination of predictors with coefficients $\beta_{0 \dots 8}$ and an additive field-level random effect α for each field which are normally distributed with mean 0 and variance $\sigma_\alpha^{\ 2}$. Residual error $\varepsilon_{i,t}$, is normal with mean 0 and variance $\sigma_\varepsilon^{\ 2}$. Models were estimated with MCMC in the R package “brms” with 3 chains of 2500 iterations after a warmup of 250 on each chain.

We used the longitudinal nature of our data to formulate a within-between approach that accounts for temporal variation within a field as well as spatial variation between fields (Van De Pol and Wright, 2009). We expect that the adoption of higher-complexity crop rotations is confounded with biophysical and socioeconomic factors such that the relationship between RCI and yield may be masked in a simple correlation. For instance, Socolar et al. (2021) showed that higher RCI is associated with lower land quality, and while we account for this relationship here via an interaction with NCCPI, other factors are not known or cannot be accounted for with available data (e.g. fertilizer and pesticide use). We therefore decompose rotational complexity (RCI) into two components: a site mean across all corn years for that field ("baseline RCI," with subscript *(m)* for "mean"), and the deviation between the year's observation and the site mean ("yearly deviation in RCI" with subscript *(w)* for "within"). This within-between approach capitalizes on variation in RCI over time within a site. Under this formulation, the effect of the baseline RCI and the baseline RCI interactions with July maximum VPD and NCCPI, (β_1, β_5, and β_7) are confounded with any time-invariant unmeasured field attributes, but the effects of the yearly deviation in RCI (β_2 and β_6) are not confounded with time-invariant values. Coupled with the site-level random intercept, this enables prediction of future conditions that take into account inherent field attributes for each field without confounding field-level effects and the effect of RCI.

Using domain knowledge and published research on the effect of various predictors on corn yield, we define prior distributions for the model coefficients (Table S2). We use informed priors on RCI, VPD, NCCPI, and year, with mean effects drawn from previous research. We set the standard deviation of these priors equal to the mean to ensure that priors are informative but also conservative, such that the prior distribution easily encompasses zero. The remainder of the model coefficients were fit with default, weakly informative priors as defined by the R package Stan interface, brms, used to fit the models (Bürkner et al., 2023).

We fit models by county to accommodate the fact that the relationship between crop practices and yield may vary at large spatial scales. For each county, we fit a model to all fields within that county and all adjacent counties (that county's "neighborhood"), then generate predictions and assess fit based on data from fields in the focal county. The neighborhood modeling approach allows each county's neighbors to support inference on the relationships within that county, minimizing the possibility of edge effects at county borders. This size also encompasses the full variability of a county and its neighbors, while being a small enough area to follow similar trends across space (e.g. weather, policy factors, etc.). In Figure 2, we give an example of a single focal county, Logan County, in green and its neighborhood in yellow.

2.5 Interpreting Posterior Predictions to Quantify Risk Mitigation

To characterize how yields respond to climate conditions over the study region, we generate yield predictions at every field, with associated uncertainty, under a variety of management and climate conditions. We compute posterior predictive distributions of yield directly from the posterior distributions of parameters sampled by MCMC, and interpret the posterior predictive distributions as the probabilities of future events. In each county and for each field, we generate posterior predictive distributions of yield in three VPD scenarios: July maximum VPD of 18, 20, and 22 hPa. We chose these values to encompass a range around 20 hPa, a threshold after which corn shows a clear negative response to increasing VPD (Xu et al., 2021). We combine each of these three VPD scenarios with seven levels of rotational complexity (21 total scenarios). Because the RCI scores also incorporate rates of turnover between crops, there is a range of values that correspond to a given number of crops in rotation. Here we simplify those ranges with six RCI values that are representative of 1-6 crop rotations (Table 1), as well as a seventh level that corresponds to the baseline RCI for each field.

These posteriors under each of the 21 scenarios allowed us to calculate the fraction of each distribution that was higher than 105% (upside probability) or lower than 95% (downside probability) of the field's historic average yield (Figure 1).

The 95% level is one below which a yield can dip relatively frequently, even at the scale of an entire farm operation. The federal crop insurance program does not offer coverage at that level under standard contracts because it is prohibitively expensive for most farmers. The vast majority of farmers must therefore find other ways of handling this level of risk and its financial implications for their operations. The 105% level is used in this study to provide the symmetric information on the upside, helping farmers make informed decisions on what opportunities arise from diversifying rotations.

Using these 95% downside probabilities, we then calculated absolute and relative risk mitigation scores in each weather scenario to compare hypothetical management under low vs high RCI. We define absolute risk as the difference in downside probabilities between two rotations while relative risk divides the absolute risk by the downside probability for the lower RCI (Figure S2). Under these definitions, positive values for risk mitigation represent situations where the more diverse rotation has reduced risk compared to the simpler rotation. We define analogous absolute and relative opportunity scores using 105% upside, instead of 95% downside, probabilities. These risk mitigation and opportunity increase scores can be calculated to compare different levels of RCI across the three weather scenarios. We report risk and opportunity scores comparing RCI values corresponding to

2-crop vs 3-crop rotations, representing the dominant rotation in the region and a modest increase, respectively.

2.6 Model Validation

A natural measure of predictive power for Bayesian models is empirical coverage probability (ECP). For each field-year with yield observations in each focal county, we predict 95% credible intervals of yield, then calculate the proportion of fields whose observed values lie within their credible interval in each county (Figure S11). After calculating risk mitigation and opportunity scores for individual fields, county-level summaries of downside and upside posterior probabilities exclude fields where the scenarios have limited real-world relevance (e.g. the downside probability is near zero and the event is unlikely to occur; see 'Criteria for field exclusions' in Supplement).

3. Results

We begin with a summary of coefficients from neighborhood models, then focus on a single field as an example to illustrate field-level predictions. We conclude with county-level aggregations of field-level results to illustrate larger spatial patterns of risk and opportunities.

3.1 Coefficient estimation from Bayesian models

Relationships between yield and RCI , along with other key predictors, vary across Illinois and Minnesota (Figure 3). As expected, July Maximum VPD has a strong negative impact on yield while year and NCCPI have positive effects (Figures S8 and S10). A field's baseline RCI typically correlates negatively with yield, while field-level increases from baseline RCI tend to correlate positively (Figure S9). The interactions between July Maximum VPD and RCI (both baseline and deviations from that baseline) span negative and positive coefficient values across counties in Illinois. In Minnesota, baseline RCI and VPD interactions tend to be positive, while within-field deviations from that baseline nearly always show a negative interaction with VPD.

3.2 Field-level risk mitigation and opportunity increase

We focus on results for a single field within Logan County, Illinois to demonstrate the basic unit of results across the two-state region. Results from this neighborhood model (see Methods and Figure 2) show that baseline RCI has a small negative effect on yield ([-0.069, -0.043] 95% CI); however, yearly deviation from the field baseline RCI has a positive effect on yield of twice the magnitude ([0.103, 0.122] 95% CI, see Table S3 for full results). In other words, increasing rotational complexity year-to-year on a given field in this county increases corn yields, while on average the fields with the highest RCI are associated with slight yield declines (likely due to confounders discussed above). Coefficients for interaction terms between decomposed RCI terms and July Max VPD are positive ([-0.001, 0.015] and [0.073, 0.094] 95% CIs for baseline and deviation, respectively), meaning that higher RCI is associated with higher yield as VPD increases across the county, and also on individual fields. As expected, July Maximum VPD has a large negative effect on yield, with one standard deviation increase in July Maximum VPD (~5 hPa) decreasing yield by 2.01 Mg ha^{-1} ([-2.020, -2.007] 95% CI). Corn yield increases both over time (year) and with better land quality (NCCPI).

After fitting our Bayesian model over the neighborhood, we then predict 95% downside and 105% upside probabilities for each field in the focal county under the 21 weather-by-RCI scenarios (Table 1). For example, in one arbitrary field, our model predicts that with an RCI of 2.24 (2 crop rotation) in normal conditions (VPD=18), the downside probability (i.e. chance of falling below 95% median field yield) is 21.3% and the upside probability (i.e. chance of yields over 105% median field yield) is 46.9%. Within a given weather scenario, as rotational complexity increases, the 95% downside probability decreases and the 105% upside probability increases, for example to 14.7% (downside probability) and 57.0% (upside probability) for a 6 crop rotation in the same arbitrary field. This means that rotation diversification reduces the probability of low corn yields and increases the probability of high corn yields, relative to the median yield for that field.

From these predicted probabilities, we calculate absolute and relative risk mitigation scores to compare two contrasting rotations. We use the scenario representing two crops as the simple rotation, S, and the scenario representing three crops as the more diverse rotation, D (Table 1).

We then summarize risk scores from each individual field to show effects of shifting from simplified to more diverse rotations over the entire county (Figure 2). Nearly all fields in Logan County show benefits from the more complex rotation in this comparison, with increased absolute risk mitigation as weather becomes more dry, while relative risk mitigation stays approximately the same. Specifically, moving from a 2-crop rotation to a 3-crop rotation decreases risk of corn yield losses in 90% of the fields in this county (Table S4).

Similarly for 105% upside probabilities, absolute and relative opportunity scores show the change in bumper crop opportunity when increasing rotational complexity, both within the sample field (Table 1) and summaries of fields across the county (Figure 2). Nearly all fields in Logan County show benefits from the more complex rotation, with relative opportunity scores increasing as weather becomes drier, and absolute opportunity scores remaining consistent between the weather scenarios.

3.3 County-level summaries of risk mitigation and opportunity increase

We repeat the field-level steps above to summarize risk and opportunity scores at the county level for all counties. County-level median risk mitigation scores represent the risk mitigation an "average" farmer would experience when comparing lower vs. higher rotational complexity. For instance, Logan County's median absolute risk mitigation score of 0.0497 in dry conditions (Figure 2) means an average field in this county has a ~5% absolute reduction in the probability of low corn yields when rotating three crops instead of two.

Across all weather conditions, all modeled counties in Illinois have positive median absolute and relative risk mitigation scores, meaning that the majority of fields will have reduced risk when using the more complex rotation (Figure 4a, S5). In contrast, median absolute and relative risk mitigation scores in Minnesota are generally positive in normal conditions, nearly zero in somewhat dry conditions, and slightly negative in dry conditions.

We also summarize results at the county level by showing the proportion of fields in a county that have absolute or relative risk mitigation above a certain threshold. Figure 4b shows a threshold of 0, indicating the proportion of fields in each county that benefit from using the more complex rotation in each weather scenario. Nearly all counties in Illinois have over 90% of fields with predicted risk reduction when using the more complex rotation. Modeled counties of Minnesota have a high proportion of fields that show risk mitigation in normal conditions, which decreases as conditions dry. Other thresholds can be chosen to reflect a desired level of risk mitigation (see Figure 5 in Discussion).

Summarizing absolute and relative opportunity scores (Figures S6 and S7) shows similar patterns over the study area. Throughout Illinois, using a more complex rotation is associated with increased probability of bumper crops (i.e. yields higher than historic field averages), particularly in drier conditions, while Minnesota shows increases in upside potential for more complex rotations in normal–but not the driest–conditions.

4. Discussion

With water deficits already causing the highest losses of crop yields seen in U.S. grain systems (Choi et al., 2024) and in other agricultural systems globally (Caparas et al., 2021), it is imperative to identify agricultural adaptation strategies that reduce future risks from drier and hotter climates. Commonly discussed risk management strategies at the level of field management often include crop and cultivar choice (Zabel et al., 2021) and irrigation adoption (Rosa, 2022), with less attention given to the potential for changes in cropping systems. Our study shows that cropping system diversification should also be considered an important adaptation strategy.

After modeling responses to contrasting rotational complexities and varying drought conditions across 393,000 fields in Illinois and Minnesota, we find that on average, increased crop rotational complexity mitigates the risk of low yields and increases the probability of high yields in normal weather conditions. Prior evidence for yield benefits of crop rotation has come primarily from long-term experiments, including recent syntheses (Bowles et al., 2020; MacLaren et al., 2022; Smith et al., 2023). While such randomized controlled trials have high validity, they also have low generalizability since they cannot represent the heterogeneity present across vast agricultural landscapes and commercial farming operations. Some studies have leveraged remotely-sensed or other data available from commercial farming operations to assess yield impacts of crop rotation (Seifert et al., 2017; Beal Cohen et al., 2019; Kluger et al., 2022), but have only narrowly defined crop rotation as the shift from monocultures to two-crop rotations and report estimates of mean benefits rather than predicting full distributions. Experimental studies suggest that major environmental and economic benefits of crop rotation only manifest at higher levels of crop rotation diversity (Smith et al., 2008; Davis et al., 2012), which we capture here with changes in RCI representative of a shift from two to three-crop rotations and beyond. We additionally generate posterior predictive distributions to better understand the full range of yield outcomes and their associated probabilities, allowing comparisons not just of mean results, but the probability of falling above or below key field-level yield thresholds.

In addition to yield benefits in typical weather, we establish benefits of crop rotation as growing conditions become drier across a large region. Patterns from county-level summaries of field-scale models include increased benefit (more fields showing decreased risk and increased opportunity) from rotation in dry conditions in areas where dry weather occurs more frequently. In Illinois, where drier summer weather (i.e. July VPD >20 hPa in >40% of corn fields) occurred in nearly half of the years of our dataset (Supplemental Table S5 and Figure S1), rotation diversification consistently and often markedly reduced risks of low yields during drier weather. Responses differ in Minnesota, where rotational diversification appears to reduce corn yields slightly as conditions become drier, and these drier years only occur half as frequently as they do in Illinois

Similar to the general effects of crop rotation on yields, prior research on yield effects of rotational diversity during stressful weather has relied on simulations (Teixeira et al., 2018), a single field site (Degani et al., 2019), or a handful of research stations (Bowles et al., 2020; Marini et al., 2020). We offer the first analysis of risk reduction with rotational complexity in adverse weather conditions that uses data from working farm fields that cover a wide range of Midwestern cropland. This analysis increases understanding of the relationship between rotational complexity and dry weather, as well as the variation in these relationships across space, in turn providing a basis for actionable information for decision-makers. The variation in relationships between rotational complexity and drought across counties, and additional variation in field-level results, points to the need for location-specific knowledge when predicting risk reduction from rotational complexity, which becomes all the more relevant with the added interaction of adverse weather events like drought. In the future, the model framework presented here could be extended by adding spatially structured error, spatially varying effects, or additional fine-scale covariate information to improve the local accuracy of field-specific recommendations.

4.1 Possible mechanisms underlying rotation effects and spatial heterogeneity

Several possible mechanisms may explain why rotational diversification increases corn yields generally, and sometimes increases yields during dry growing conditions. In favorable growing conditions, well-documented benefits of more diverse grain rotations include greater nitrogen availability from legumes (MacLaren et al., 2022); breaking life cycles of weeds, herbivorous insects and plant pathogens (Bennett et al., 2012; Weisberger et al., 2021); resource complementarity across different different crops (Liebman and Dyck, 1993); and improvements in soil health (Ball et al., 2005). Additional mechanisms that may be particularly relevant during dry growing conditions include changes in soil organic matter and soil structure that lead to greater water availability (Schmer et al., 2020; Blanchy et al., 2023), which could both increase crop access to water and allow nutrient cycling to persist (Bowles et al., 2022). Shifts in microbial communities also occur with rotation diversification, including greater abundances of arbuscular mycorrhizal fungi (Bowles et al., 2017; Mooshammer et al., 2022), a group of fungal symbionts with known roles in supporting plant performance during dry conditions.

These mechanisms also point at potential explanations for the spatial heterogeneity observed in rotation's benefits. For example, variation in pest pressure across space may enhance or lessen the benefits seen from rotation in different areas, with areas of the lowest and highest pressure not displaying a strong response to rotation. Similarly the interaction of rotation and dry weather may be more pronounced in areas with relatively low soil organic matter content, a possibility that is consistent with the lower rotation by dry weather interaction in Minnesota, where soils generally have higher levels of organic carbon than Illinois (Guevara et al., 2020).

4.2 Challenges and Limitations

Farmers make decisions regarding the level of crop diversity based on markets as well as climate, soil, topographical, and other landscape features. For example, Socolar et al. (2021) showed that diversified rotations are more likely to be present on land with lower inherent quality and with lower mean annual precipitation. Further, highly-simplified monoculture or two-crop rotations rely on a system of industrial agriculture that typically includes higher levels of synthetic fertilizer and pesticide inputs compared to those in diversified rotations (Davis et al., 2012). These inputs influence both crop yields and their response to rotational diversity. For example, the yield benefits of rotation are lower when fertilizer inputs are high (Bowles et al., 2020; MacLaren et al., 2022). Thus, these factors confound results when not explicitly included in models, resulting in predicted negative correlations between rotational diversity and crop yields. While we were able to include a metric of land quality and dry weather conditions in our model, agricultural input data (fertilizers and pesticides) and crop variety are not available at the field scale and therefore pose a challenge as they cannot be included in yield models.

Rather than attempting to include all possible confounders in our models, largely due to a lack of available data, we chose to split RCI into a baseline level (historic field average) and annual deviation from this baseline (i.e. "within RCI") to accommodate potential confounders. These confounders' presence is likely reflected in the negative coefficient for field mean RCI across most counties in Illinois and Minnesota (Figure 3). Negative effects of crop rotation on corn yields would be contrary to most published research from long-term experiments from corn-based cropping systems in the same region (Bowles et al., 2020; Smith et al., 2023), as well as other observational studies that have focused on a more limited definition of crop rotation (i.e. shifting from monoculture corn to a corn-soybean rotation) (Seifert et al., 2017; Beal Cohen et al., 2019; Kluger et al., 2022). We believe our current model to be consistent with this previous work while also accommodating the existence of potential confounding variables in the model. Under the assumption that confounders remain constant in a given field across the study period, our model is able to isolate how corn yields respond to changing rotational complexity in a given field. Development of field-level datasets on input use, crop varieties, and landscape factors could reduce these assumptions and provide a more mechanistic understanding of the conditions in which rotations improve yields and mitigate risks.

We use RCI to quantify rotational diversity; however, it is not an exact proxy for the benefits expected from increasingly diverse rotations (Socolar et al., 2021). Importantly, it does not distinguish between crop functional groups (assuming instead that farmers choose their crops in rotation with purpose and knowledge of functional benefits). It also forces a distinction (i.e. quantitatively different scores) between patterns of rotation that may not represent a functional difference in rotational benefit. With this in mind, we limit predictions to comparing RCIs that represent 2 vs 3 crop rotations, a large enough difference to encompass a meaningful change in RCI while not suggesting unrealistically large shifts in farmer decision-making.

4.3 Policy implications

While our study does not account for differences in economic returns across rotation patterns, it is likely that the current integration of USDA program crops in global supply chains and federal program supports increase the relative profitability and appeal of simpler rotations (Secchi et al., 2011; Claassen et al., 2017; Roesch-McNally et al., 2018; Burchfield et al., 2022). The U.S. Congress has continued to show an increased awareness of the benefits, both internal and external to the farming system, of sustainable agricultural practices. Currently, through programs offered by the USDA's Natural Resource Conservation Service (NRCS), there is federal support for roughly 200 conservation practices (USDA, 2024).

However, diversified crop rotations, like those in this study, are not among the practices funded through NRCS programs, perhaps due to a lack of robust research that demonstrates the benefits to the farm and the broader agricultural economy. Findings in this study demonstrate the need for continued evidence-based research that shows the value that diversifying crop rotations can have on agricultural production risks and the rest of the agricultural economy. Other work in this area is also needed to underscore the importance of federal funding to support increased rotations by also considering prices and returns and the long-term impacts of the status quo.

While yields of key cash crops are an important piece of farm profitability, production costs and crop prices across entire rotations add crucial context to analyses of farm risk and practice adoption that are not captured in our current corn yield-based model. As production costs in more diverse rotations tend to be lower (Singh et al., 2021), and yields in dry years may increase, farms with diversified rotations could attain similar or higher profits compared to farms with simplified rotation. However, given the lower frequency of corn inherent in more diverse rotations, diversified farms may not be able to match profits that simplified rotations achieve as long as corn prices remain inflated by their use in animal feed and biofuel (Marsh, 2005; Parcell and Westhoff, 2006) and markets for typical additions to corn-soy rotations (e.g. small grains) cannot provide comparable profits.

Current policy also complicates the potential increase in profits diversified farms could realize from decreased yield losses in dry years. Crop prices rise during droughts (Leister et al., 2015), in theory giving farmers with more diverse rotations in Illinois higher gross revenues than peers with simplified rotations. However, heavily subsidized insurance policies that protect against losses in yields or revenues shrink–or even reverse–the gap in profitability that would otherwise reward diversified farms (Bowman and Zilberman, 2013; Roesch-McNally et al., 2018). In these ways potential practice adoption motivators (i.e. increased profits and revenues) and financial benefits to taxpayers (decreased indemnity payments) are limited by current economic and policy landscapes.

We can use the models presented above to examine thresholds of rotational benefits that may be relevant to different farming and policy applications. For example in Figure 5 we ask which counties demonstrate risk mitigation that "moves the needle" to an extent that might be meaningful for a farmer or insurer (5% relative increase in risk mitigation), and identify counties that would most benefit from widespread adoption of more complex rotations. A major benefit of these modeling efforts is the ability to provide spatially tailored recommendations for farmers to adopt practices in areas where they are most likely to succeed, and for insurers and lenders to use this information to quantify and reward less risky behavior across heterogeneous landscapes.

The costs of climate risks to crop production are enormous. In the U.S. alone, the cost of crop insurance indemnity payouts has increased by over 500% since the early 2000s due mainly to weather-related losses, with 2022 the most expensive year on record for crop insurance payouts (Schechinger, 2023b). Extreme weather is increasingly leading to farm bankruptcies that harm families and reverberate throughout rural communities across the globe (Garrido and Gómez-Ramos, 2000; Ding et al., 2011; Kingwell and Payne, 2015; Newton, 2020), while production risks associated with adverse weather conditions are the top risk affecting agricultural lenders in the US (Office of the Comptroller of the Currency, 2018). Within these same insurance and lending sectors lie opportunities for rewarding farmers for changes to management that reduce production risks. Globally, tools that can accurately assess agricultural risk are being called for to finance climate resilient transformations of food systems (Millan et al., 2019). If lenders and insurers had metrics to understand the relative and absolute risk mitigation of practices like crop rotation, as well as a spatially explicit understanding of where these benefits are most likely to occur, this information could be translated into pricing and terms on loans and insurance policies that more accurately reflect actual risks. The value of this risk reduction could then be passed onto farmers who use or shift to more diversified cropping systems, promoting additional environmental and economic co-benefits.

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Tables and Figures

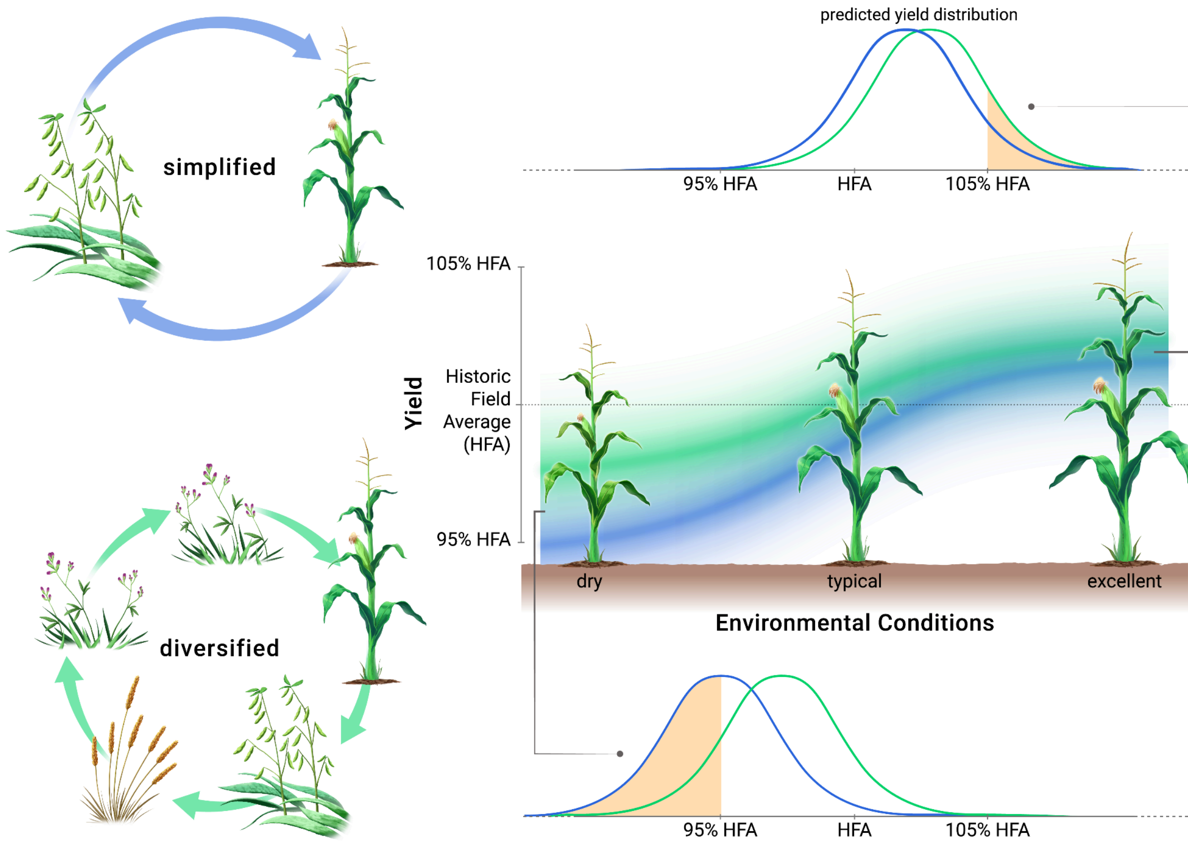


Figure 1. Summary of our approach and definitions of key concepts. We compare crop yields in simplified vs diversified rotations in increasingly dry years. Here we show hypothetical predicted yield distributions for a single field under a simple rotation (blue) and a more diverse rotation (green). In dry conditions we highlight that the simplified rotation has a greater chance of performing worse than 95% of the field's historical yield average (downside probability) than the diversified rotation (comparing areas shaded in orange), while in excellent environmental conditions the diversified rotation has a greater chance of performing better than 105% of the field's historic average (upside probability). We define the differences in downside and upside probabilities between simplified and diversified rotations as risk and opportunity scores, respectively.

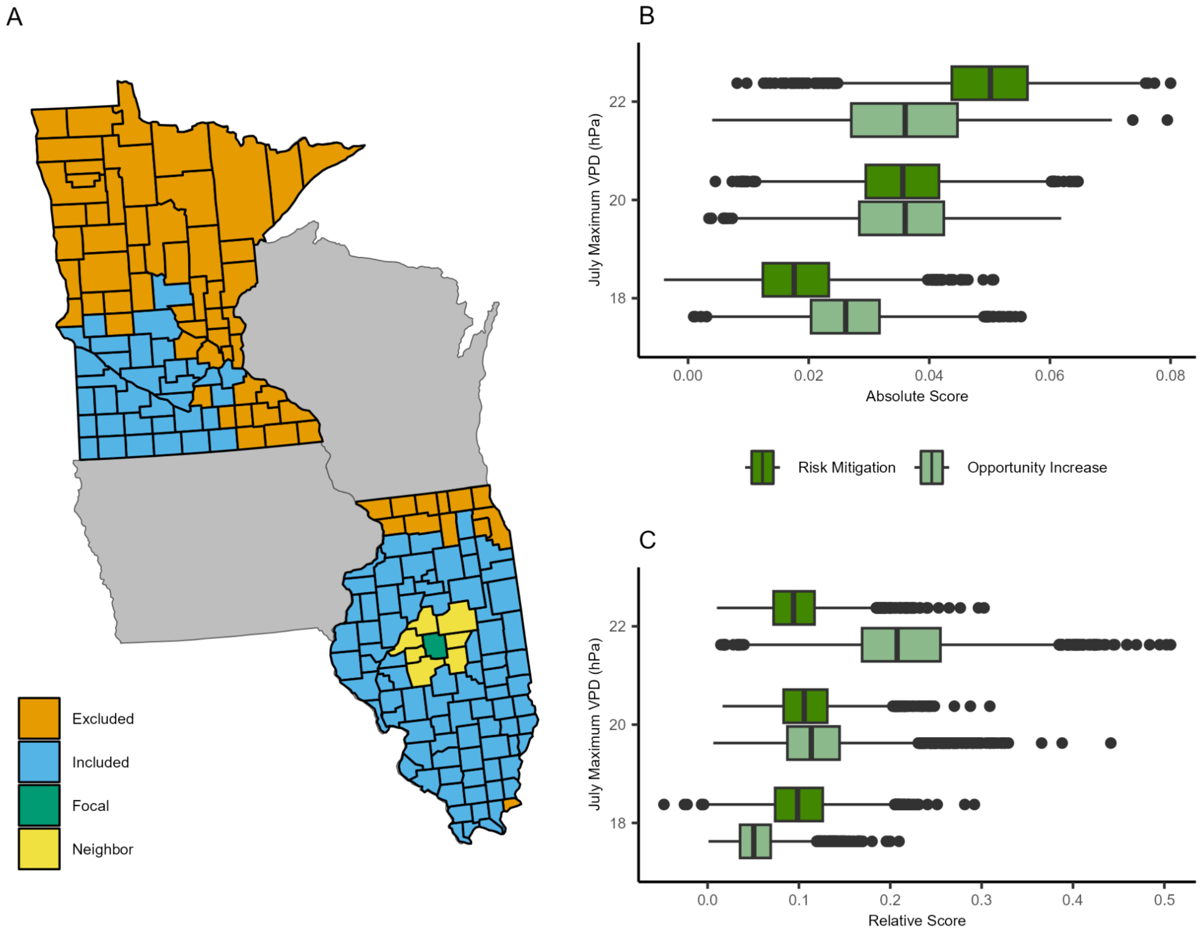


Figure 2. Illinois and Minnesota counties included and excluded in the analysis. Each county shown in blue was the focal county for a model fit, which also included surrounding counties (i.e. the neighborhood). For example, a focal county, Logan County, IL, is shown in green with its associated neighborhood in yellow. Box plots show the distribution of B) absolute and C) relative risk mitigation and opportunity scores, for all fields in Logan County, comparing a more diverse rotation (RCI of 3.1) vs. a simpler rotation (RCI of 2.24). Absolute scores show reduction of probability of having lower than 95% of average yields (risk) or increase in probability of having higher than 105% of average yields (opportunity) in diverse vs simplified rotations. Relative scores divide the absolute risk/opportunity for diverse rotation by the total downside/upside probability for simplified rotations (see Figure S2). Higher VPD indicates drier conditions.

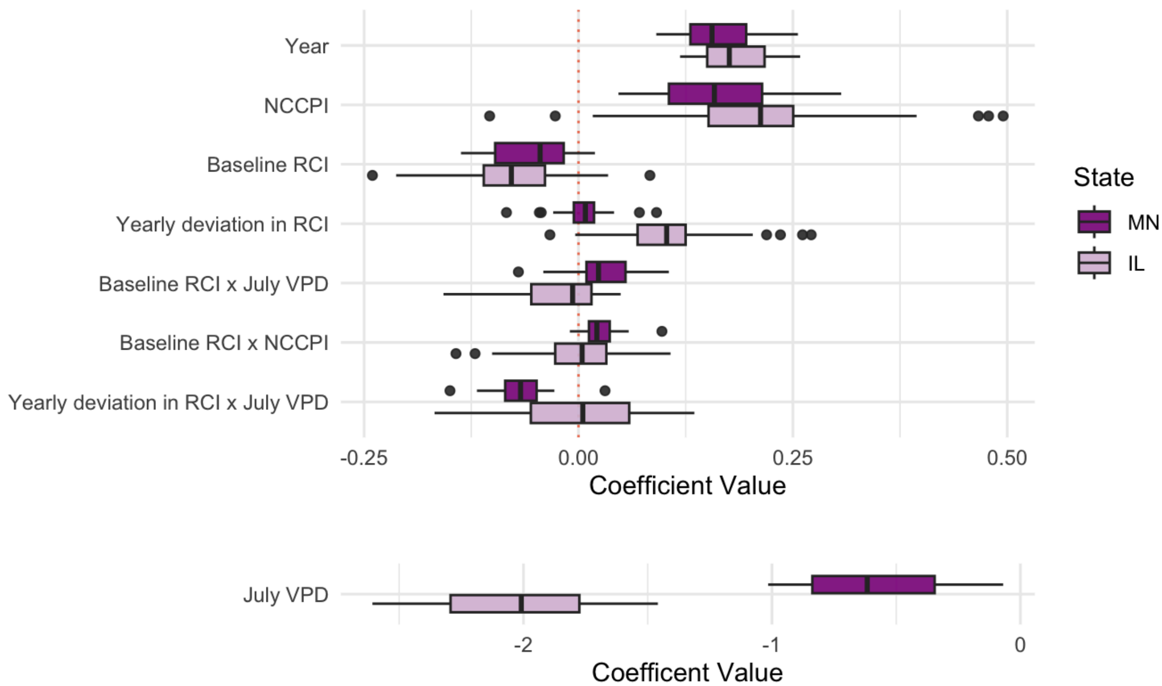


Figure 3. Box plots of coefficient estimates for all model predictors by county, separated by state. Here each box plot represents the distribution of coefficient estimates for the given variable over all modeled counties in the corresponding state. Note that July VPD (average maximum) is shown on a separate axis with a different scale. All predictors were standardized by neighborhood before running models.

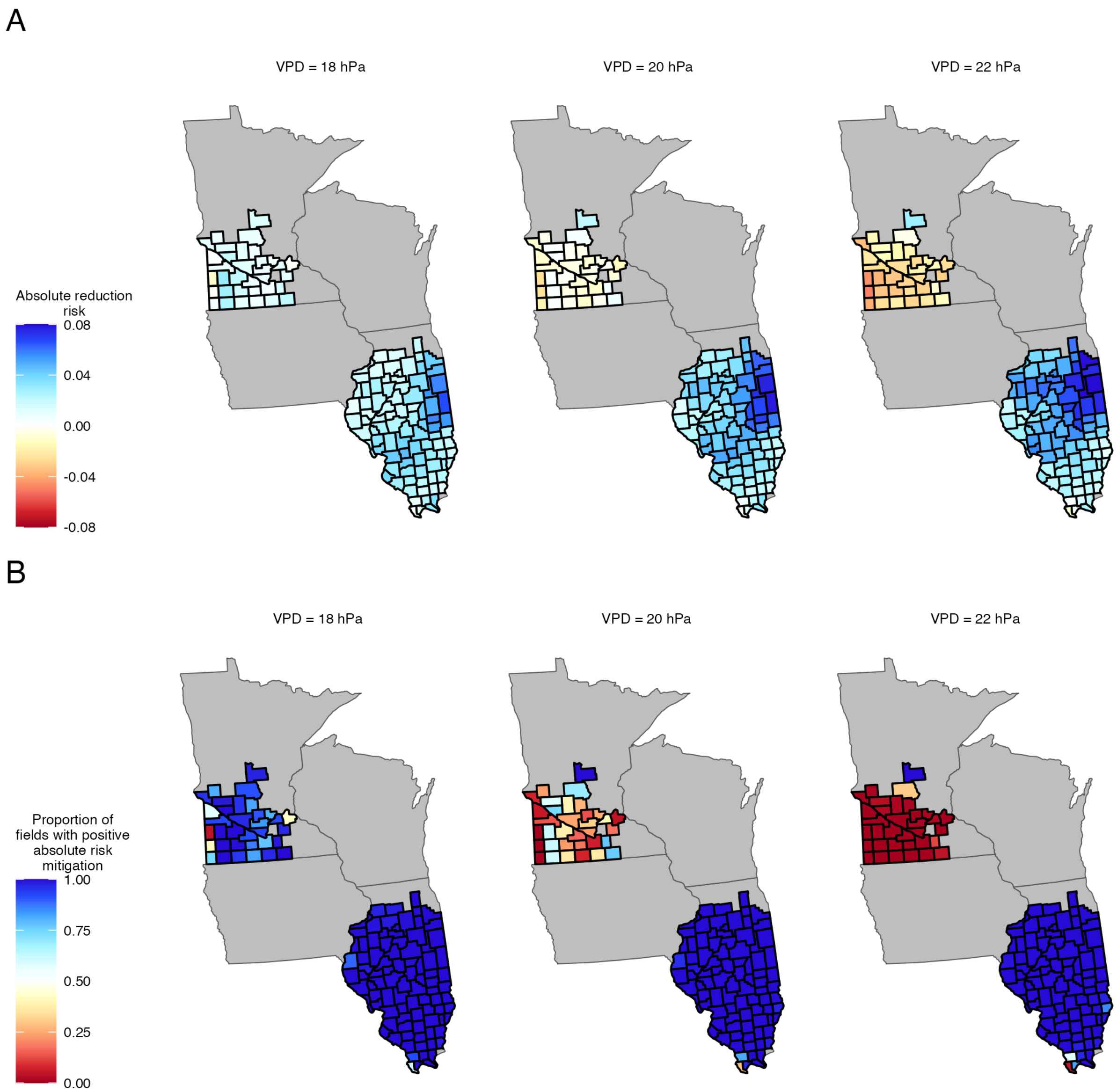


Figure 4. Risk mitigation metrics. Panel A shows median absolute risk mitigation score for all fields in a county when using a 3-crop rotation instead of a 2-crop rotation for that field, at a VPD of 18 (left), 20 (middle), and 22 (right). This shows the absolute risk reduction the "average" field will experience. Panel B shows the proportion of fields per county that have positive absolute risk mitigation scores when using a 3-crop rotation instead of a 2-crop rotation (i.e. more complex rotation mitigates risk). Higher VPD indicates drier conditions.

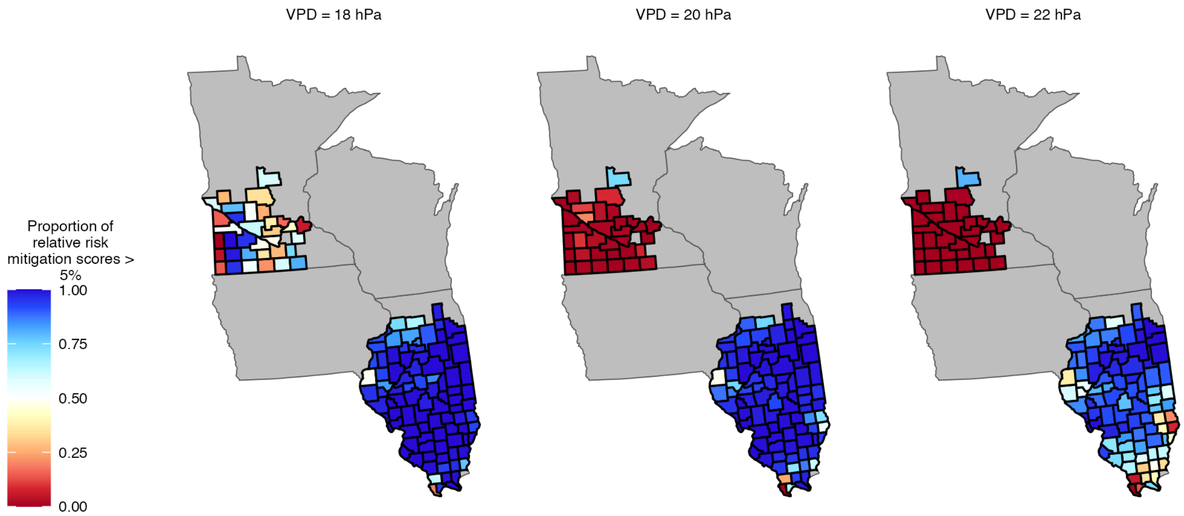


Figure 5. The proportion of fields per county that have relative risk mitigation scores greater than 5% when using a 3-crop rotation instead of a 2-crop rotation at a VPD of 18 (left), 20 (middle) and 22 (right). Relative risk is defined as the absolute risk of a given field divided by the 95% downside probability under low RCI. Where Figure 4B focuses on whether risk scores are above zero (i.e. does the probability of a field yielding lower/higher than 95%/105% of its historical average improve *at all* for diverse vs simplified rotations), here we use a threshold of 5% relative risk mitigation, showing the proportion of fields in each county where diversified rotations offer a >5% reduction in risk relative to a simplified rotation. Higher VPD indicates drier conditions.

Representative RCI used for prediction	Number of Crops in Rotation (in a 6-year period)	VPD (hPa)	95% Downside Probability	105% Upside Probability	Absolute Risk Mitigation Score (2 vs 3 crop) $d_S - d_D$	Relative Risk Mitigation Score (2 vs 3 crop) $(d_S - d_D)/d_S$	Absolute Opportunity Increase Score (2 vs 3 crop) $u_D - u_S$	Relative Opportunity Increase Score (2 vs 3 crop) $(u_D - u_S)/u_S$
0	1 Crop	18	0.270	0.397				
2.24	2 Crops	18	0.213	0.469	0.213 - 0.193 = 0.02	(0.213 - 0.193)/ 0.213 = 0.094	0.030	0.064
3.1	3 Crops	18	0.193	0.499				
3.95	4 Crops	18	0.174	0.515				
4.5	5 Crops	18	0.151	0.552				
5.2	6 Crops	18	0.147	0.570				
	Historical Field Average (2 Crops)	18	0.212	0.472				
0	1 Crop	20	0.521	0.176				
2.24	2 Crops	20	0.409	0.257	0.038	0.093	0.041	0.159
3.1	3 Crops	20	0.371	0.298				

3.95	4 Crops	20	0.341	0.318				
4.5	5 Crops	20	0.310	0.348				
5.2	6 Crops	20	0.286	0.373				
	Historical Field Average (2 Crops)	20	0.411	0.251				
0	1 Crop	22	0.761	0.058				
2.24	2 Crops	22	0.645	0.099	0.065	0.101	0.038	0.384
3.1	3 Crops	22	0.580	0.137				
3.95	4 Crops	22	0.525	0.166				
4.5	5 Crops	22	0.504	0.186				
5.2	6 Crops	22	0.461	0.216				
	Historical Field Average (2 Crops)	22	0.637	0.107				

Table 1. 95% downside and 105% upside probabilities in each prediction scenario for a sample field in Logan County. Within each VPD condition, we include predictions using the field average RCI to represent the downside and upside probabilities under current management. While we report the number of crops this RCI average might represent, the actual number of crops in rotation may be slightly different given how RCI is calculated (Socolar et al 2021). Calculated absolute and relative risk mitigation and opportunity scores for the sample field are shown comparing a 3-crop rotation over a 2-crop rotation. Higher VPD indicates drier conditions.

Supplemental Materials

Datasets

Variable	Description	Resolution	Source
Corn yield	Corn yield maps derived from the Scalable Crop Yield Mapper (SCYM)	30m	Lobell et al. (2015)
Rotational Complexity Index (RCI)	Value representing the complexity of the crop rotation over the prior six-year period, based on the number and turnover of cash crop species	Field (boundaries from Yan & Roy, 2016)	Socolar et al. (2021)
National Commodity Crop Productivity Index (NCCPI)	Proxy for land quality	30m	gSSURGO, USDA NRCS (2016)
Maximum Vapor pressure deficit (VPD)	Indicator of water stress for corn. Difference (deficit) between the amount of moisture in the air and how much moisture the air can hold when it is saturated	4 km, collected daily	PRISM Climate Group

Table S1. Variables included in statistical model with associated description, spatial resolution, and data source.

SCYM Performance

Since farmer-reported field-level corn yield data are not publicly available, we used corn yield maps derived from the Scalable Crop Yield Mapper (SCYM) (Jin et al., 2017; Lobell et al., 2015). SCYM was chosen for yield data estimation due to its high accuracy and extensive validation at both field and county scales (Deines et al., 2021; Jin et al., 2017). For instance, when compared with 100,000s of observations from tractor-based yield monitor data, SCYM showed an R^2 of 0.45 at the field level, with disagreements likely due to data artifacts in both the yield monitor and satellite sources. When compared with NASS county-level data, SCYM had an R^2 of 0.69 (Deines et al., 2021). However, it is important to acknowledge that discrepancies in SCYM's yield estimates, when compared with yield monitor data, will introduce noise into our analysis. These discrepancies are likely a result of data artifacts present in both satellite and yield monitor sources. While this noise could affect the precision of our yield predictions, the unbiased nature of SCYM regarding crop rotation and management practices ensures that yield estimates across different rotational systems are comparable and not systematically skewed. Compared to other approaches that use remote sensing and modeling to estimate yields, SCYM estimates are the most accurate and have the best spatiotemporal coverage (Deines et al., 2021; Kang & Özdoğan, 2019). Other analyses have used SCYM-derived yield maps to evaluate the yield impacts of conservation agriculture practices including two-crop vs. monoculture rotations (Beal Cohen et al., 2019), as well as cover cropping (Deines et al., 2023) and reduced tillage (Deines et al., 2019).

County inclusion criteria

To ensure sufficient modeling sample sizes, predictor variation, and scale of downside and upside probabilities, we imposed various restrictions on our modeling and prediction. First, the minimum sample size for a county is 500 data points (field-years) to avoid attempting to fit a model on counties with very few fields. The minimum number of fields modeled in a county is 143 and the median is 3013.

Second, since July maximum VPD is our primary weather predictor and we are predicting for values between 18 and 22 hPa, we conservatively chose to only model and predict for counties where the average July maximum VPD over the county has exceeded 21 hPa in any single year over the course of the study period, (excluding 2012, an extremely dry year). Past research has shown (Xu et al 2021) that the detrimental effect of July maximum VPD on corn yield is approximately linear between 20 and 40 hPa whereas VPD levels below 20 hPa have minimal effect. This restriction allows modeling for all of Illinois and most of southern Minnesota.

After following these inclusion criteria, we were left with 125 counties in our analysis (Figure 2).

Priors

Based on previous studies, we expect an increase of one unit in RCI to be associated with an increase in maize yield of 0.22 - 0.3 Mg ha^{-1} (Bowles et al, 2020, Seifert et. al. 2017). Therefore, for the coefficients for RCI, β_1 and β_2, we set a normal prior with mean and standard deviation of 0.26 kg ha^{-1}. Similarly, the detrimental effect of July Maximum VPD on corn is approximately linear between 20 and 40 hPa and corresponds to a decrease in yield of 2.2 - 6 Mg ha^{-1} (Xu et. al., 2021). Therefore, an increase of one hPa in July Maximum VPD is associated with a decrease in yield of approximately 0.2 Mg ha^{-1} and we set a normal prior for β_3 with mean and standard deviation of -0.2 Mg ha^{-1}. Soil quality, as represented in our model by NCCPI, is known to have a positive impact on yield, with an increase of 1 in NCCPI corresponding to an increase in yield of 1.1 - 1.2 Mg ha^{-1} (Deines et. al., 2021). We thus set a prior for NCCPI with mean and standard deviation of 1.15 Mg ha^{-1}. Finally, corn yield is known to increase over time due to advances in farming technology, at a rate of approximately 0.15

Mg ha^{-1} per year (Cassman & Grassini, 2020). We then set a similar prior for β_8 with a mean and standard deviation of 0.15 Mg ha^{-1}.

Variable	Distribution	Prior mean	Prior SD
RCI	Gaussian	0.26 kg ha^{-1}	0.26 kg ha^{-1}
VPD	Gaussian	-0.2 Mg ha^{-1}	-0.2 Mg ha^{-1}
NCCPI	Gaussian	1.15 Mg ha^{-1}	1.15 Mg ha^{-1}
Year	Gaussian	0.15 Mg ha^{-1}	0.15 Mg ha^{-1}
Intercept	Gaussian	22.5 Mg ha^{-1}	5 Mg ha^{-1}
Interactions	Improper flat prior		
Random effect and residual standard deviations	Student t on 3 degrees of freedom	0 Mg ha^{-1}	3.477 Mg ha^{-1}

Table S2. Priors used in each county-neighborhood model.

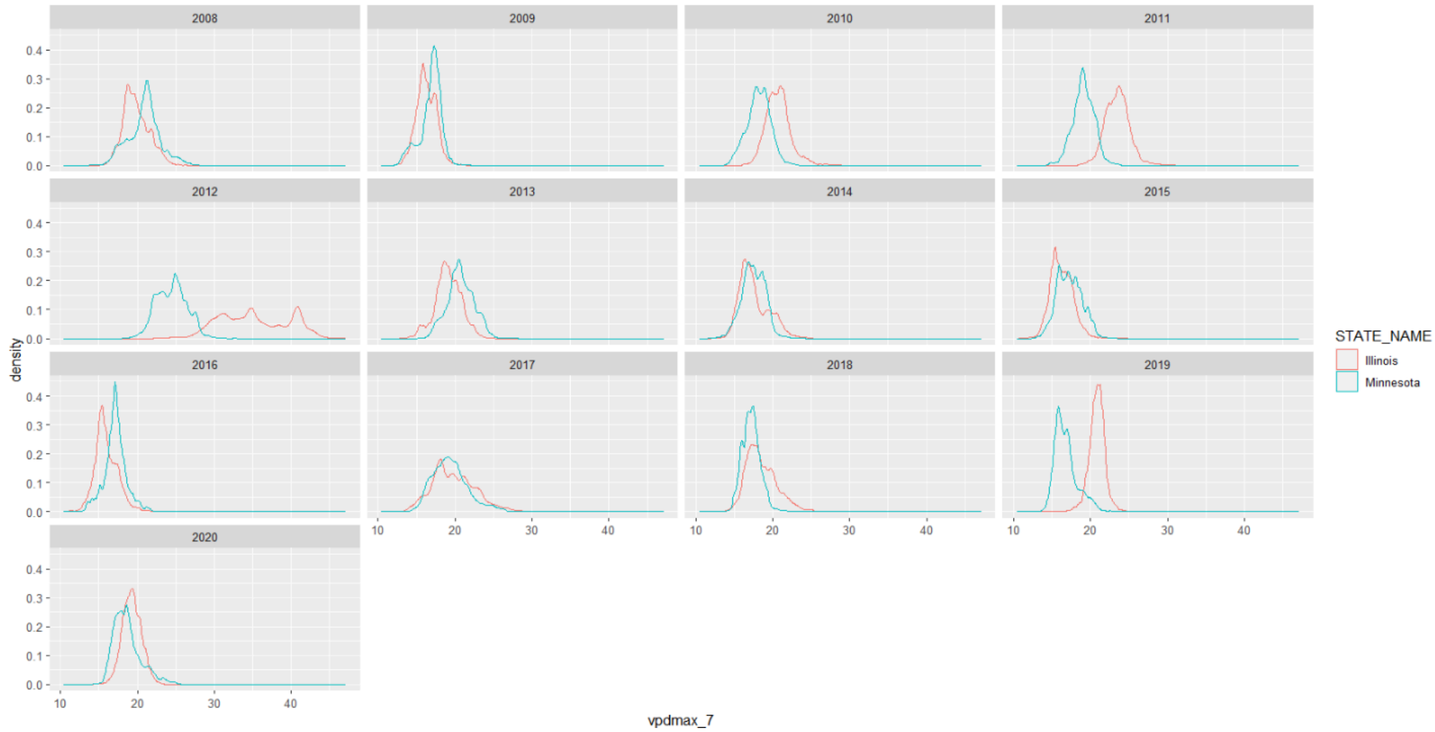


Figure S1. Density plots for maximum July VPD by state and year.

Absolute and Relative Risk and Opportunity Scores

For absolute risk, let d_S and d_D be the 95% downside probability for a chosen field in a given VPD condition, under simple (low RCI) and diverse (high RCI) crop rotation, respectively. The absolute risk mitigation offered by increasing from the simple rotation to the more diverse rotation for this field is d_S - d_D. We then defined the relative risk mitigation as $(d_S - d_D)/d_S$

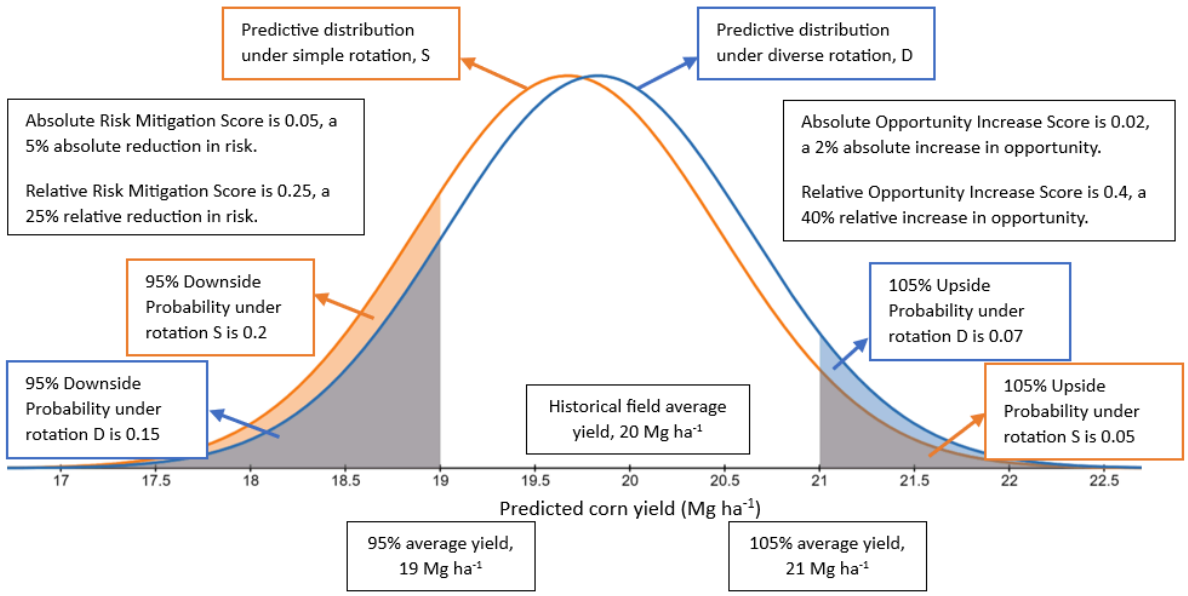


Figure S2. Hypothetical predicted (i.e. posterior) yield distributions for a single field under a simple rotation (orange) and a more diverse rotation (blue). This field has a historical average of 20 Mg ha^{-1} making the cutoffs for 95% and 105% historical average yield 19 and 21 Mg ha^{-1}, respectively (note that yields are reported in total biomass, rather than grain yield). The simple rotation has 95% downside probability of $d_S = 0.2$ whereas the diverse rotation has a smaller 95% downside probability $d_D = 0.15$, corresponding to an absolute risk mitigation score of $d_S - d_D = 0.2 - 0.15 - 0.05$ or a 5% absolute reduction in risk, and a relative risk mitigation score of $(d_S - d_D)/d_S = (0.2 - 0.15)/0.2 = 0.25$, or a 25% relative reduction in risk. Similarly, the simple rotation has a 105% upside probability of $u_S = 0.05$ whereas the diverse rotation has a larger 105% upside probability $u_D = 0.07$, corresponding to an absolute opportunity increase score of $u_D - u_S = 0.07 - 0.05 = 0.02$ or a 2% absolute increase in opportunity, and a relative opportunity increase score of $(u_D - u_S)/u_S = (0.07 - 0.05)/0.05 = 0.4$, or a 40% relative increase in opportunity.

Criteria for field exclusions from county-level summaries

After calculating risk mitigation and opportunity scores for individual fields, county-level summaries of downside and upside posterior probabilities exclude fields from each county whenever the downside or upside probability predictions fall outside of [0.05, 0.95]. The justification for this choice of which fields to exclude is two-fold. First, downside and upside probabilities on the tails of the distribution (i.e. the bottom 5% and top 5% of the posterior predictive distribution) are less accurate (more prone to relative errors in estimating chances of events) than those in the bulk of the distribution. Further, these extreme probabilities are less meaningful for farmers and insurers when comparing practices, and would generate misleading relative risk mitigation and opportunity scores. For example, suppose that in a given field for a given adverse weather scenario, our model predicts 99% downside probability (probability of falling below 95% average field yield) under a simple rotation and 98% downside probability under a more diverse rotation. This would result in absolute risk mitigation of 1% and relative risk mitigation score of approximately 1%. In both these scenarios, the downside event is nearly certain to occur, and the management system becomes irrelevant. On the opportunity side, suppose that for this field, under an unfavorable weather scenario, the upside probability (probability of achieving above 105% average field yield) is 1% under a simple rotation, and is 2% under a more diverse rotation. This would result in an absolute opportunity increase of 1% and relative opportunity score of 100%. However, the chance of achieving this upside is negligible in both scenarios, so the difference between the management systems also becomes irrelevant, and reporting a 100% opportunity score would be highly misleading. The reader can imagine examples of scenarios for both upside and downside probabilities where the tails are reversed compared to the above two scenarios, and the conclusions of avoiding those fields in any reports and county-level summaries remains the same. Thus, in order to avoid all these extremes, we exclude these tail probabilities. We report the proportion of fields per county which are excluded by this restriction (Figure S3, S4).

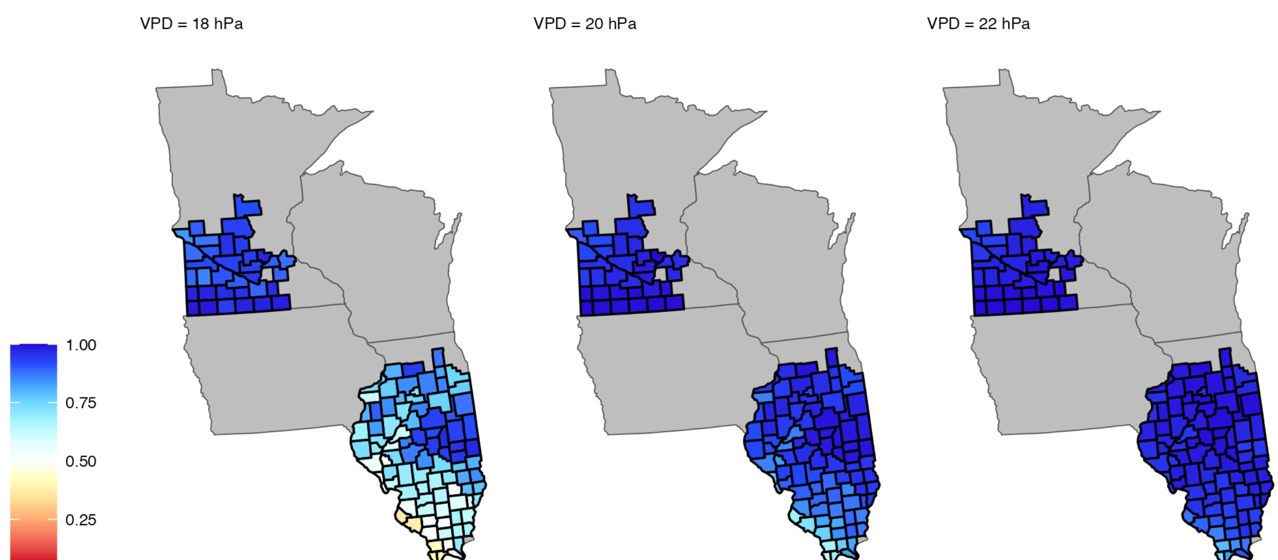


Figure S3. Proportion of fields included when reporting risk scores. Excluded fields have extreme downside probabilities (less than 5% or greater than 95%). For example, a VPD of 18 hPa in southern Illinois represents relatively favorable growing conditions so falling below 95% median field yield is highly improbable for many fields.

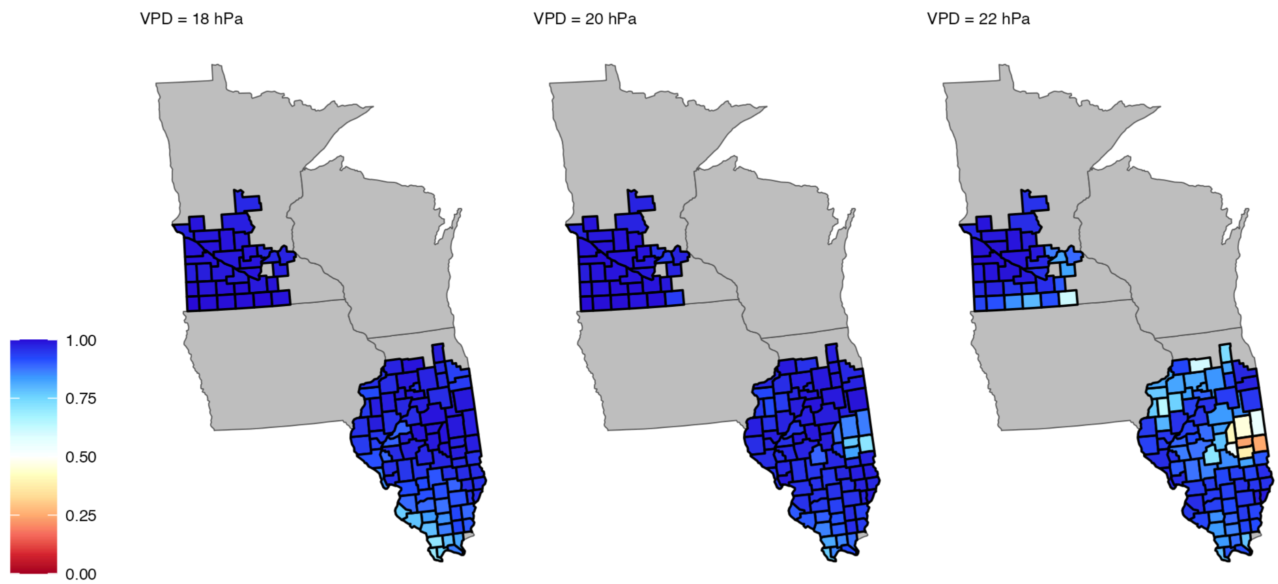


Figure S4 Proportion of fields included when reporting opportunity scores. Excluded fields have extreme upside probabilities (less than 5% or greater than 95%). For example, a VPD of 22 hPa in central Illinois represents relatively dry growing conditions that are very likely to be detrimental to corn yield, so achieving above 105% median field yield is improbable for many fields.

County-level model results (Logan County)

Parameter	Estimate (Mg ha^{-1})	Est. Error	95% Credible Interval
Intercept	10.907	0.006	(10.896, 10.919)
Baseline RCI	-0.056	0.006	(-0.069, -0.043)
Yearly deviation from baseline RCI	0.113	0.005	(0.103, 0.122)
NCCPI	0.210	0.005	(0.201, 0.220)
July VPD Max	-2.014	0.003	(-2.020, -2.007)
Year	0.218	0.001	(0.217, 0.220)
Yearly deviation from baseline RCI x July VPD Max	0.084	0.005	(0.073, 0.094)
Baseline RCI x July VPD Max	0.007	0.004	(-0.001, 0.015)

Baseline RCI x NCCPI	0.065	0.005	(0.054, 0.075)
sigma	1.407	0.002	(1.403, 1.412)

Table S3. Coefficient estimates, estimated error, and 95% credible intervals for model coefficients in Logan County. All predictor variables are standardized, so the coefficient estimate represents the change in yield associated with an increase of one standard deviation in the predictor variable.

County-level risk percentiles

Percentile	10th	20th	30th	40th	50th	60th	70th	80th	90th	NA
Normal	0.0057	0.0097	0.0127	0.0153	0.018	0.021	0.024	0.028	0.034	223
Somewhat Dry	0.0193	0.0253	0.0297	0.0327	0.036	0.0393	0.043	0.0467	0.0527	41
Dry	0.031	0.0377	0.042	0.0457	0.0497	0.053	0.0567	0.0613	0.067	23

Table S4. Percentiles of absolute risk mitigation scores when using a 3 crop rotation instead of a 2 crop rotation for Logan County under each weather scenario. Note that the number of fields excluded due to downside probabilities outside of [0.05,0.95] is given under NA. For example, there are 223 fields without relative risk scores under normal conditions because in normal conditions, many fields have a chance of falling below 95% median field yield that is below 5%.

Year	State	Percentage of fields growing corn with July Max VPD < 18hPa	Percentage of fields growing corn with July Max VPD between 18 and 20 hPa	Percentage of fields growing corn with July Max VPD >20 hPa
2008	Illinois	10.96	47.96	**41.08**
2008	Minnesota	10.34	18.23	**71.43**

2009	Illinois	92.49	7.11	0.40
2009	Minnesota	83.23	16.13	0.63
2010	Illinois	2.99	31.29	**65.72**
2010	Minnesota	44.21	45.44	10.35
2011	Illinois	0.02	1.42	**98.56**
2011	Minnesota	19.80	54.08	26.12
2012	Illinois	0.00	0.00	**100.00**
2012	Minnesota	0.00	0.77	**99.23**
2013	Illinois	23.18	46.61	30.20
2013	Minnesota	6.68	26.58	**66.74**
2014	Illinois	67.10	18.71	14.19
2014	Minnesota	62.09	34.85	3.06
2015	Illinois	89.08	9.90	1.02
2015	Minnesota	66.57	28.23	5.20
2016	Illinois	91.08	7.71	1.21
2016	Minnesota	78.08	18.49	3.42
2017	Illinois	27.64	28.17	**44.18**
2017	Minnesota	29.09	35.74	35.17
2018	Illinois	46.25	32.36	21.39
2018	Minnesota	77.77	20.96	1.27
2019	Illinois	0.88	16.45	**82.66**
2019	Minnesota	82.20	13.67	4.13
2020	Illinois	14.21	57.91	27.88
2020	Minnesota	40.33	40.17	19.50

Table S5. Percentage of corn fields in given VPD ranges across all states and years included in the dataset.

Relative Risk

When comparing the three weather scenarios, median absolute risk mitigation tends to increase throughout IL as VPD increases. The relationship between median relative risk mitigation scores and VPD follows the opposite trend. This is partially due to the magnitude of downside probabilities in each condition. That is, drier conditions have larger downside probabilities, and therefore the same absolute reduction in risk has a smaller relative magnitude compared to the magnitude of the downside probability.

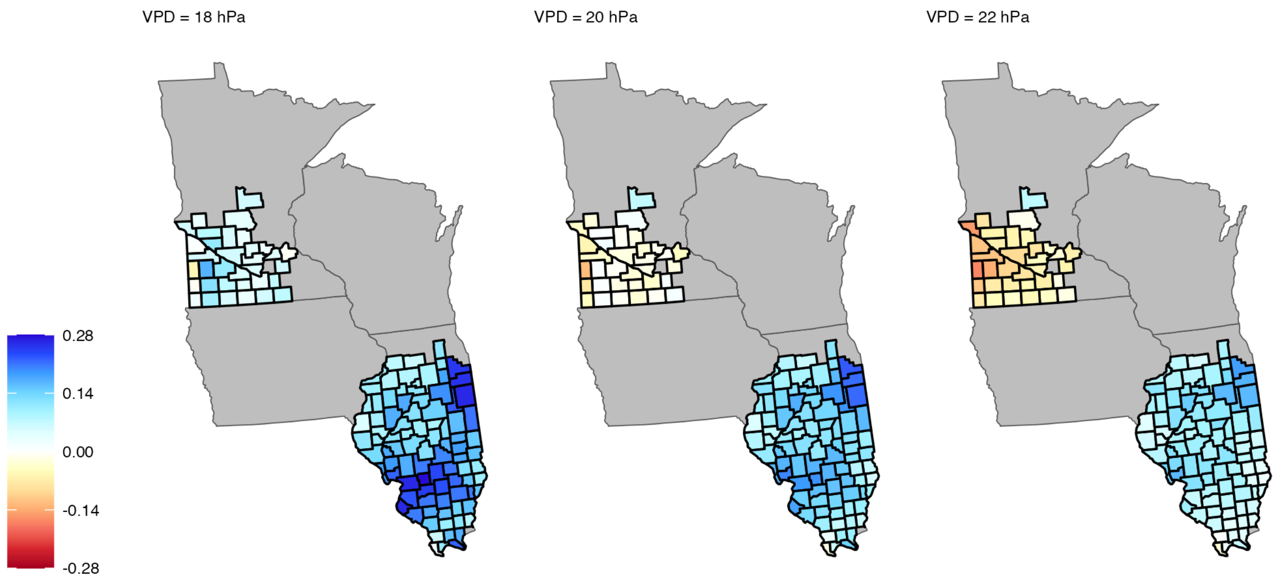


Figure S5. Median relative risk mitigation for all fields in a county when using a 3-crop rotation instead of a 2-crop rotation for that field, at VPD of 18 (left), 20 (middle), and 22 (right). See Figure 4A in main text for absolute risk reduction.

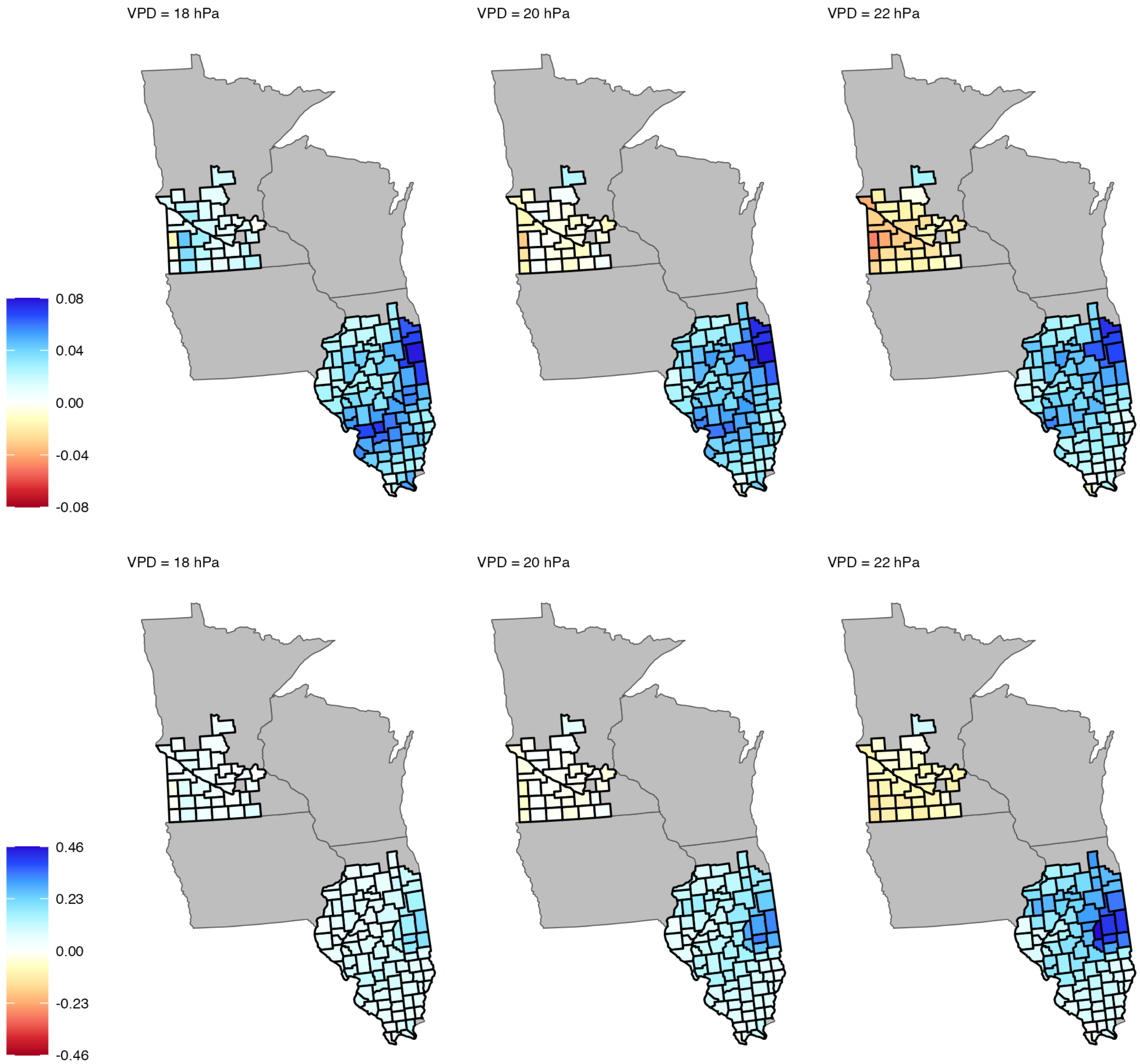


Figure S6. Median absolute (top) and relative (bottom) opportunity increase for all fields in a county when using a 3-crop rotation instead of a 2-crop rotation for that field, at a VPD of 18 (left), 20 (middle), and 22 (right). This shows the absolute and relative opportunity increase an "average" field in each county will experience.

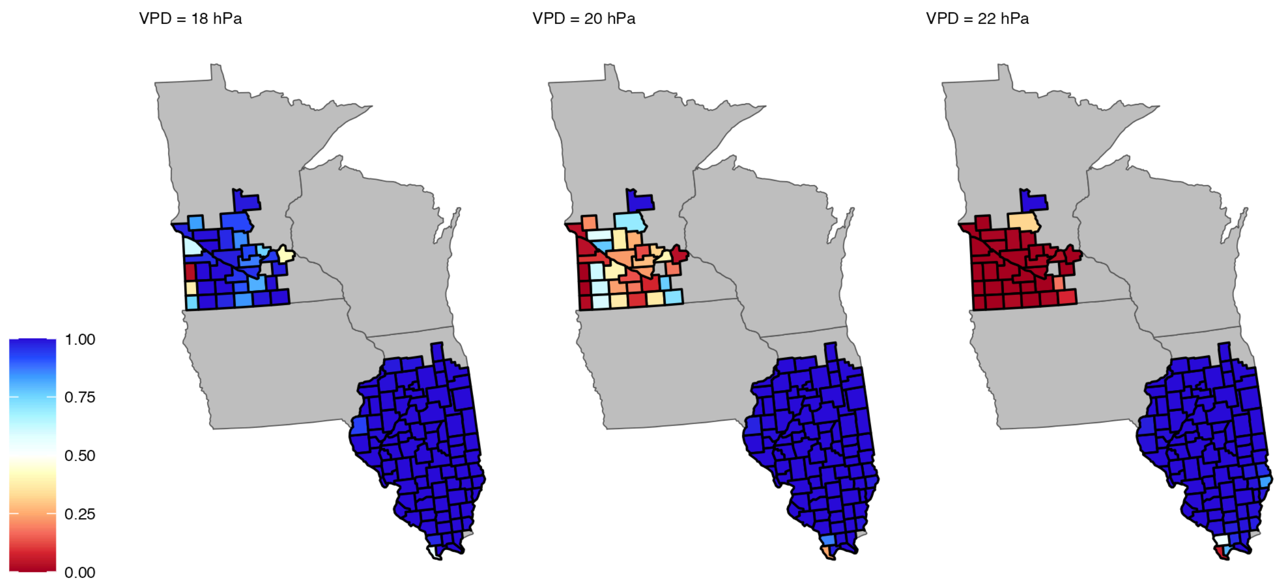


Figure S7. The proportion of fields per county that have positive absolute and relative opportunity increase scores when using a 3-crop rotation instead of a 2-crop rotation. Note that by definition, a positive absolute opportunity increase score implies a positive relative opportunity increase score.

Presentation and interpretation of model coefficients by county

The Bayesian estimates for model coefficients show regional patterns in the relationships between rotational complexity, water stress, soil quality and yield. For example, July Maximum VPD has a strong negative effect on yield (Figure S8), with more detrimental effects occurring in the southern part of the study area. This effect is weaker in MN counties and may reflect the threshold effect of July Maximum VPD on yield, with strong negative effects only occurring above ~20 hPa, conditions that are much less common in MN than IL. Corn yield increases by approximately 0.1 - 0.3 Mg ha^{-1} per year (Figure S8), with larger increases in western IL and northern MN.

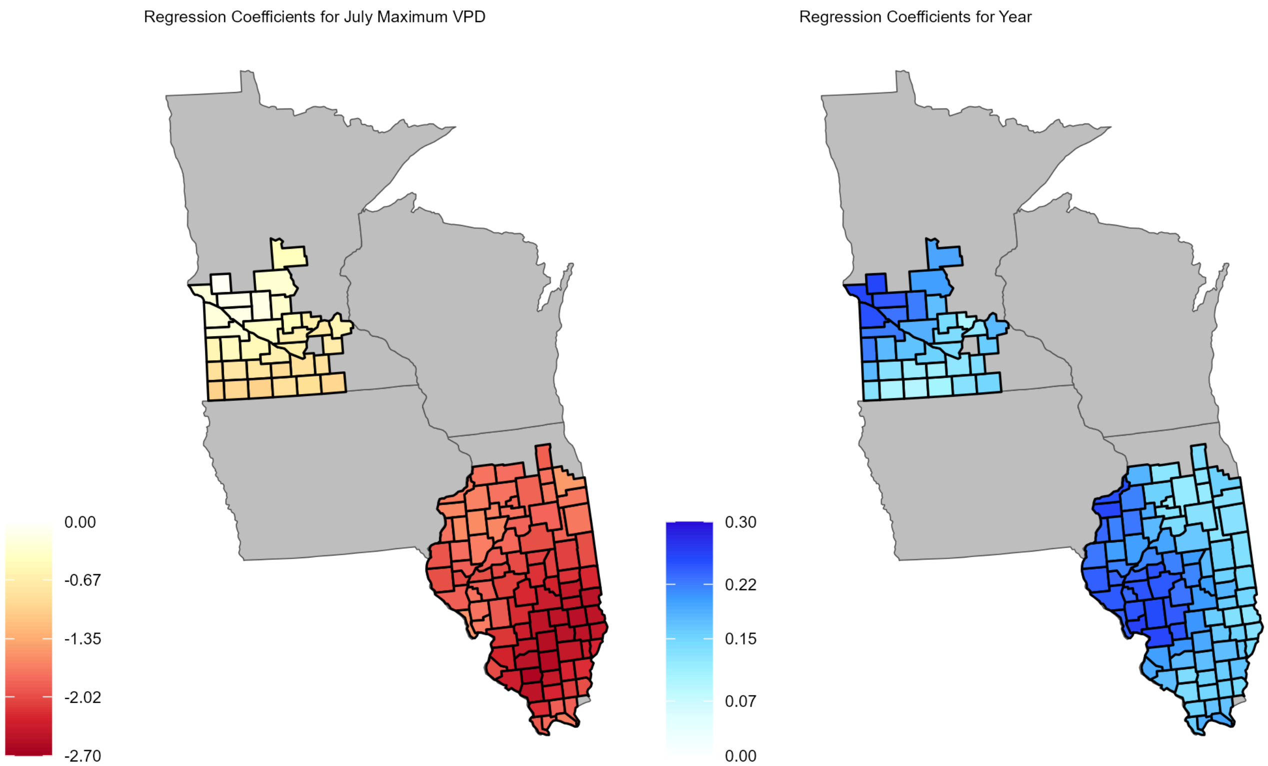


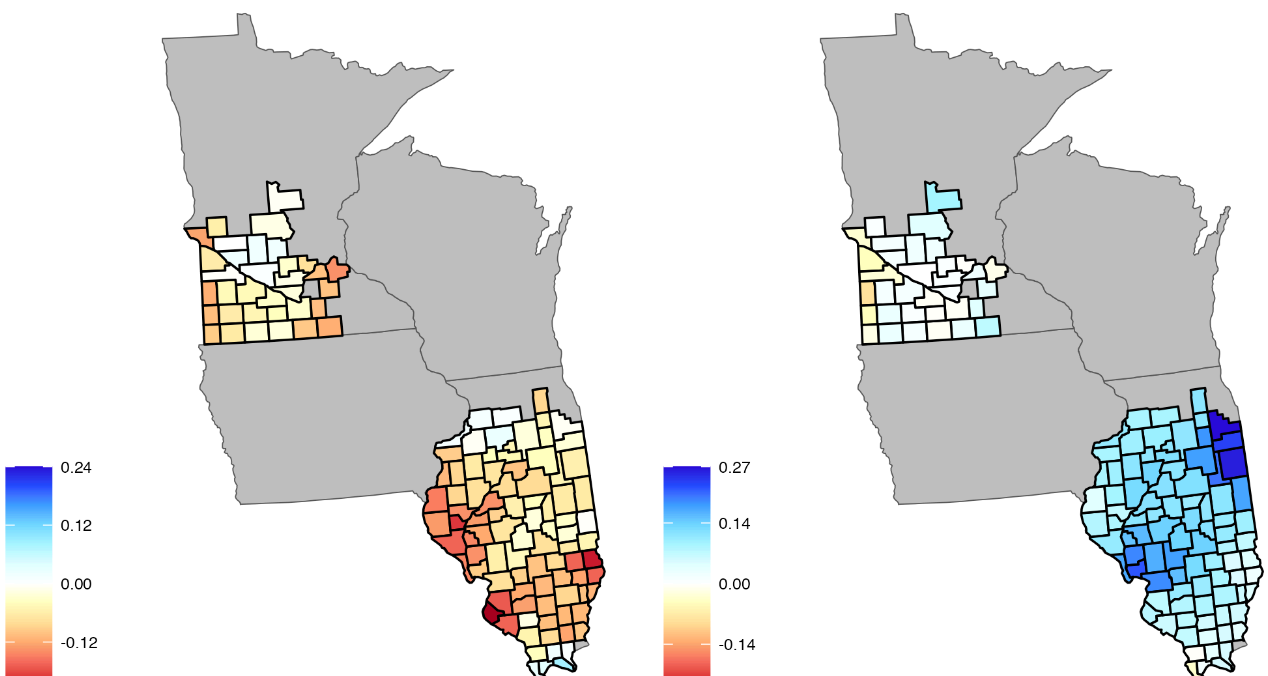
Figure S8. Heat maps of Bayesian coefficient estimates for July Maximum VPD (left) and year (right) by county for the study area. VPD coefficients show a large detrimental effect of high July VPD on yield that increases in more Southern counties. Coefficient estimates for year show a small increase in yield over time, with greater increases in Western Illinois and the Northern portion of the studied area in Minnesota.

Small negative coefficient estimates for baseline RCI means that fields with a higher baseline rotational complexity have lower maize yields (Figure 3). This relationship may be confounded by farmers who use simplified rotations also applying fertilizers and pesticides at higher rates than their peers, as is typical in industrialized systems. By contrast, positive coefficient estimates for yearly deviations from baseline RCI shows that increasing rotational complexity within a given field is associated with a yield benefit.

County-level estimates for the interactions between RCI terms and July Maximum VPD are more variable. For the interaction between baseline RCI and VPD, when comparing fields under the same VPD conditions, positive values mean fields with higher baseline RCI will have higher yields (i.e. reduced risk) during water stress. As July Maximum VPD increases, this reduction in risk also increases. Northern and central IL as well as modeled counties in MN tend to have positive values. For the interaction between yearly deviation from baseline RCI and July Maximum VPD, when comparing fields under the same VPD conditions, positive values mean fields with larger RCI increases year-to-year will have higher yields (i.e. reduced risk) during water stress, with this risk reduction increasing as VPD increases. Northern and central IL tend to have positive values (Figure S9).

Regression Coefficient Estimates for the Baseline RCI

Regression Coefficient Estimates for the Yearly Deviation in RCI



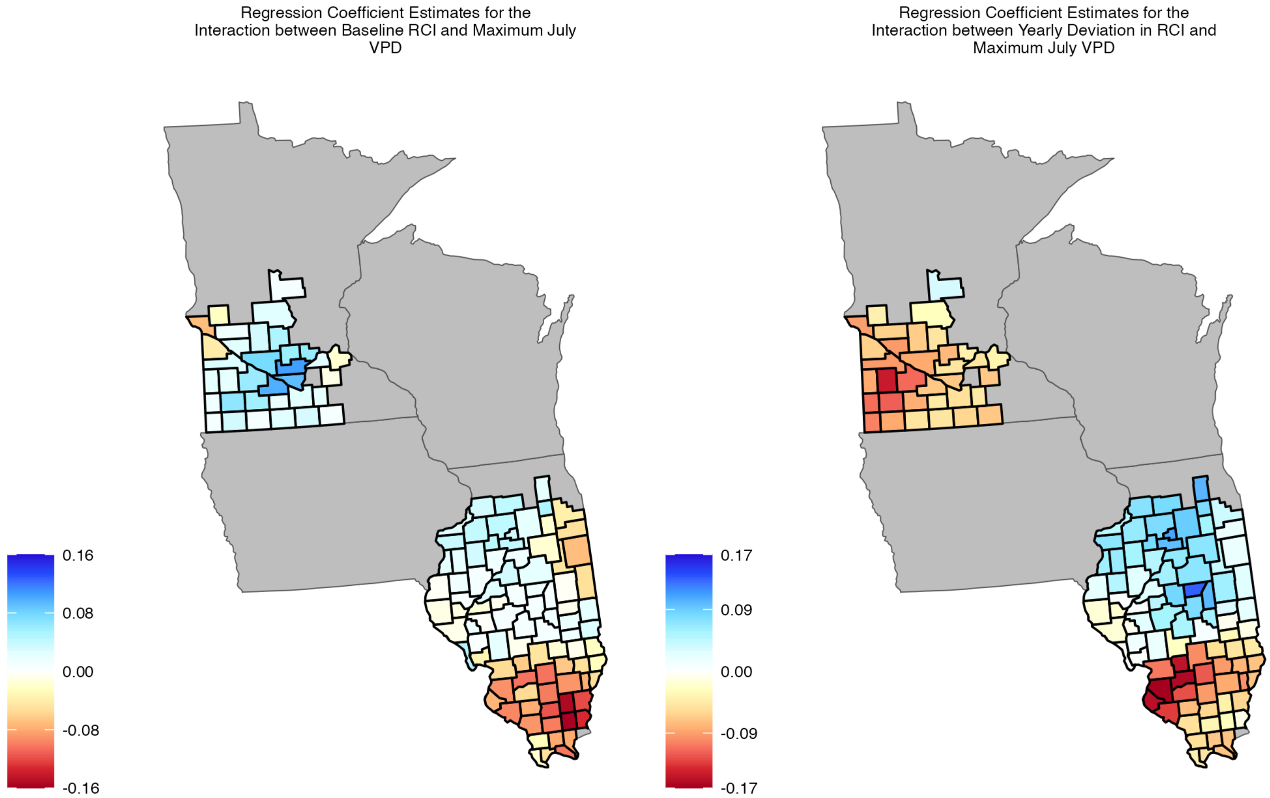


Figure S9. Heat maps of coefficient estimates for baseline RCI (top left) and changes in RCI (top right), as well as their interaction with July Maximum VPD (bottom left and right, respectively).

Finally, higher landsoil quality (NCCPI) is associated with increased yield (Figure S10). In central to northern IL and in MN when comparing fields with the same soil quality, fields with a higher baseline RCI have an associated small increase in yield.

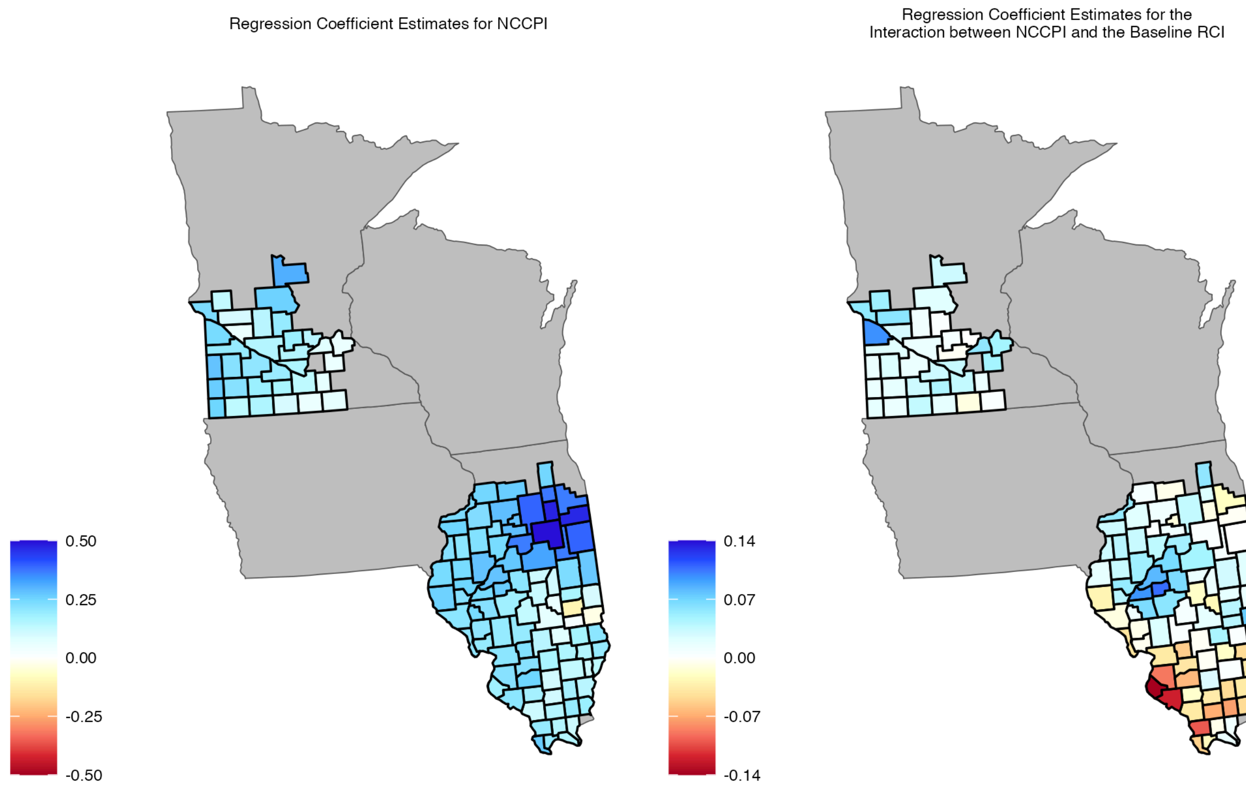


Figure S10. Heat maps of coefficients for NCCPI (left) and the interaction between NCCPI and baseline RCI (right). As expected, higher land quality is associated with increased yield. In Central to Northern IL and in MN when comparing fields with the same soil quality, fields with a higher baseline RCI are associated with an addition small increase in yield.

Model validation Metrics

To evaluate the accuracy of model predictions, we calculate empirical coverage probability (ECP) for prediction in each county using observed data for predictors. Figure S9 shows the empirical coverage probability by county for 95% credible intervals. This is extremely accurate uncertainty quantification, as all coverage probabilities are near the nominal level of 0.95. In this figure, there is almost no under reporting (i.e. coverage probability less than 95%) so we can feel confident we are not giving a false sense of accuracy. In counties with above the nominal level, we err on the side of conservative estimates. With these results, we can be confident in the accuracy and honesty of our uncertainty quantification.

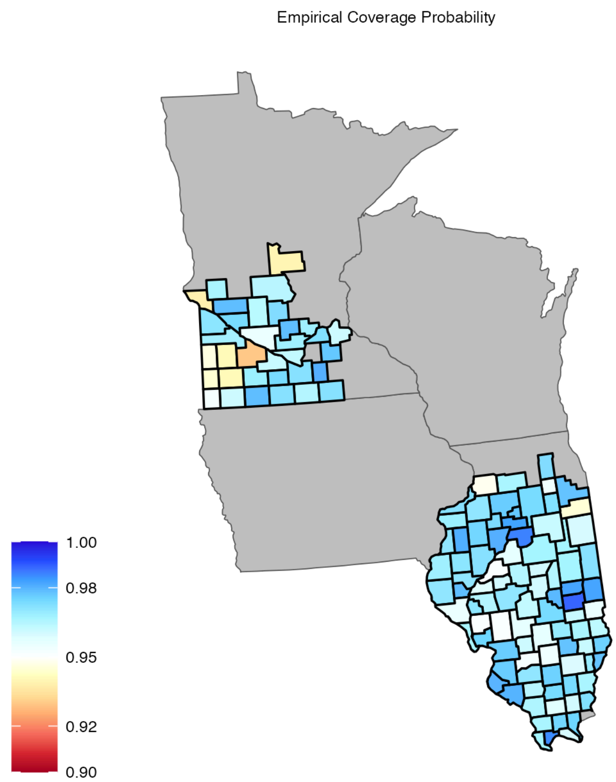


Figure S11. The empirical coverage probability for prediction in a single county. That is, the proportion of actual yield data observations that fall within 95% credible intervals for yield created through model prediction using observed data for predictors. The best model performance, in terms of predictive accuracy, is when the proportion of data points which fall in a 95% credible interval is as close as possible to the 95% nominal level. When those proportions are close, the credible intervals can also be used to assess model fit: credible intervals narrow enough to be unambiguous to the user about the predictions, providing them with actionable information, would represent a good fit in practice.

Supplement References

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