Title: Recent cover crop adoption is associated with small maize and soybean yield losses in the United States

Running title: Yield impacts of cover crops in the Corn Belt

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Abstract

Cover crops are gaining traction in many agricultural regions, partly driven by increased public subsidies and by private markets for ecosystem services. These payments are motivated by environmental benefits, including improved soil health, reduced erosion, and increased soil organic carbon. However, previous work based on experimental plots or crop modeling indicates cover crops may reduce crop yields. It remains unclear, though, how recent cover crop adoption has affected productivity in commercial agricultural systems. Here we perform the first large-scale, field-level analysis of observed yield impacts from cover cropping as implemented across the US Corn Belt. We use validated satellite data products at sub-field scales to analyze maize and soybean yield outcomes for over 90,000 fields in 2019-2020. Because we lack data on cover crop species or timing, we seek to quantify yield impacts of cover cropping as currently practiced in aggregate. Using causal forests analysis, we estimate an average maize yield loss of 5.5% on fields where cover crops were used for three or more years, compared to fields that did not adopt cover cropping. Maize yield losses were larger on fields with better soil ratings, cooler mid-season temperatures, and lower spring rainfall. For soybeans, average yield losses were 3.5%, with larger impacts on fields with warmer June temperatures, lower spring and late-season rainfall, and, to a lesser extent, better soils. Estimated impacts are consistent with multiple mechanisms indicated by experimental and simulation-based studies, including effects of cover crops on nitrogen dynamics, water consumption, and soil oxygen depletion. Our results suggest a need to improve cover crop management to reduce yield penalties, and a potential need to target subsidies based on likely

yield impacts. Ultimately, avoiding substantial yield penalties is important for realizing widespread adoption and associated benefits for water quality, erosion, soil carbon, and greenhouse gas emissions.

1. Introduction

Cover cropping is a key tenet of conservation agriculture that involves planting non-cash crops on agricultural fields to provide soil cover between primary crop growing seasons. In the United States, both federal and state policies increasingly encourage seeding cover crops in the fall. For example, the United States Department of Agriculture's Environmental Quality Incentives Program (EQIP) has provided more than $100 million of incentives for cover crop adoption each year since 2016 (Wallander, Smith, Bowman, & Claassen, 2021), and the Risk Management Agency has recently added an incentive through the Pandemic Cover Crop Program (PCCP), in the form of reduced insurance premiums. The rationale for subsidizing cover crops is that maintaining some vegetation cover on agricultural fields in the off-season may provide substantial public benefits that extend well beyond the private benefits experienced by the farmer implementing the practice. Prominent among these expected benefits are (i) large reductions in runoff and leakage of nitrogen (N) into streams and groundwater, with associated reductions in health and environmental impacts, (ii) increased carbon sequestration in agricultural soils, with associated reductions in net national greenhouse gas emissions, (iii) reduced soil erosion, and (iv) reductions in chemical use for weed control (Blanco-Canqui et al., 2015; Daryanto, Fu, Wang, Jacinthe, & Zhao, 2018; Jacobs et al., 2022; Speir et al., 2022).

Overall, the number of farmers practicing cover cropping has increased in recent years, at least partly due to these recent policy incentives (Wallander et al., 2021). The total cropland area in the United States planted with cover crops in 2017 (6.2 million ha) was ~50% higher than reported in 2012 (NASS, 2021) and has continued rising in the past half-decade. Overall prevalence is low, however, at roughly 5% of cropped area in 2017.

Despite the clear policy momentum around cover crops, many questions remain about the potential consequences of a widespread shift towards this practice. Prominent among these questions are to what extent yields of the primary crops are affected by cover crops. Beneficial effects on yields could amplify some of the benefits mentioned above as well as increase farmer revenue. Negative yield effects, in contrast, could lead to subsequent abandonment of the practice and reversal of the benefits mentioned above. Even if subsidies were enough to maintain the practice in the face of yield penalties, the public benefit could be substantially reduced because of indirect effects on land use in neighboring areas (Villoria, 2019).

One approach to understanding the yield effects of cover crops has been experimental field trials. These trials often find slight yield losses for primary crops. For instance, a recent review of 106 studies across 372 sites around the world reported an average yield reduction of 4% (Abdalla et al., 2019). However, these effects appear to vary considerably depending on many factors, including the agricultural region, the combination of cover and primary crop types, weather conditions, and management practices. In reviewing experiments in North America, for example, Marcillo and Miguez (2017) reported that maize yields, on average, were unaffected by cover crops, but results varied widely based on the type of cover crop, the level of fertilization, and the date of cover crop termination. In contrast, Malone et al. (2022) found maize yield reductions of 6-9% when cover crops established successfully in the US state of Wisconsin. In experiments in the Argentinean Pampas, maize yields were reduced by 8% when following a non-legume cover crop compared to a fallow control but increased by 7% when following a legume cover crop (Alvarez, Steinbach, & De Paepe, 2017).

A second approach has been to simulate the effects of cover cropping with agroecosystem models that represent the biophysical and biochemical processes governing crop growth and soil-plant-atmosphere interactions, benchmarked and tested against field data. A recent study (Qin et al., 2021) for Illinois used the *ecosys* model to study the effects of cover crops on both maize and soybean yields. They estimated that a rye cover crop led to an average of 3.9% loss of maize yields, but with minimal effect on soybean yields. As with experimental studies, they also report a strong dependence on whether the cover crop was a legume or non-legume species, whether the field was well fertilized, and whether the cover crop was terminated early or late relative to the sowing of the primary crop.

The clear picture emerging from experiments and models is that cover crops can meaningfully affect the productivity of primary crops, but that the exact impacts will depend on the environment and the details of implementation, both of which differ from farm to farm. Thus, results from existing work may have limited external validity when pertaining to farmers' fields. The question of how much, if at all, the recent adoption of cover crops has affected productivity in commercial agricultural systems, therefore, remains largely unanswered.

In this study, we use a third approach that utilizes data from actual farmer fields, thus avoiding potential problems arising from a lack of external validity. Specifically, we deploy methods based on satellite data to observe both the adoption of cover cropping and the yields of maize and soybeans throughout six states in the heart of the U.S. Corn Belt. These observations, which span more than 90,000 fields, are then used in a causal forests analysis to measure the incremental yield impact of adopting cover crops.

2. Data and Methods

2.1 Study Area

We examined six states in the US Corn Belt that had the highest total cover cropped area based on the most recent US Agricultural Census in 2017: Iowa, Indiana, Missouri, Ohio, Illinois, and Michigan (ordered by descending cover cropped area; Fig. 1). Among these states, the "3I" states comprise the core Corn Belt characterized by high yielding, commercial-scale agriculture predominantly in maize-soybean rotation, while the states of Missouri, Ohio, and Michigan comprise typically lower-yielding outer-Corn Belt regions (Green, Kipka, David, & McMaster, 2018; NASS, 2021). Each individual state had over 270,000 ha of cover crops in 2017, with Iowa having the most area (394,000 ha). In aggregate, 5.0% of agricultural fields in our study area were cover cropped in 2017, up from 2.6% in 2012 (NASS, 2021).

Due to the low prevalence of cover cropping on the landscape and recent expansion (Fig. 1, 2), we focused on maize and soybean yield outcomes in the 2019-2020 rotation cycle. By looking at these most recent years, we were able to analyze more fields with a consistent history of cover cropping across broad environmental conditions.

2.2 Data

We identified cover crop presence at a 30 m resolution each year using a recently developed map dataset spanning 2000-2021 derived from satellite data (Figure 3) (Zhou et al., 2022). Briefly, this dataset was produced by training a machine learning model to identify annually-varying county-year specific greenness thresholds indicative of cover cropping in daily time series of vegetation greenness. The daily time series was generated at 30 m pixel resolution by fusing Landsat and MODIS satellite observations. The dynamic threshold and phenology-based approach effectively addresses the varying growth conditions of cover crops across large geographies and over different years, thus making the algorithm highly scalable and also largely avoiding confusing signals such as weed or perennial grass. Resulting pixel-level predictions of cover cropping activity were then aggregated to field boundaries, and fields with greater than 40% coverage were considered “cover cropped”. Annual estimates of cover cropped area aggregated by state are shown in Fig. 2 alongside 2012 and 2017 Census estimates. When validated against county-level percent area estimates from the 2017 Agricultural Census for counties dominated by maize and soybeans, the maps had an R^2 = 0.81 (RMSE = 1.25 percentage points). Performance was lower across all counties evaluated (R^2 = 0.63 and RMSE = 2.3 percentage points), suggesting the approach was most effective for maize and soybean fields. At the field level, the cover crop map dataset had accuracies between 65-90% when compared against opportunistic field-level ground truth data of variable quality from single counties in Illinois, Indiana, and Iowa. Field-level accuracies were positively correlated with ground dataset quality. More details on the generation and accuracy evaluation of the cover crop maps can be found in Zhou et al. (2022). In our analysis, we minimized the impact of inaccurate classifications in any year by filtering the map dataset based on multiyear classification histories for each pixel (section 2.3).

This dataset thus provides the annual presence or absence of cover crops each year at field-level resolution. It does not, however, provide information about the species of cover crop used or specify the timing of cover crop termination prior to planting of the main crop. Our analysis, therefore, represents the yield impacts of cover cropping as practiced in aggregate across the region. Based on surveys (Wallander et al., 2021), the majority of cover crops in our study area and time period are rye. The full cover crop map dataset covers 12 states in the larger Corn Belt region, excluding counties with less than 40% maize and soybeans. Available counties in our study region are displayed in Fig. 1a, b.

We obtained annual, crop-specific maize and soybean yields at 30 m resolution from previously published methods based on the Scalable Crop Yield Mapper (SCYM) algorithm (Figure 3) (Jin, Azzari, & Lobell, 2017; Lobell, Thau, Seifert, Engle, & Little, 2015). Briefly, SCYM uses region-specific crop model simulations and weather covariates to interpret remotely sensed crop phenology for each satellite pixel, thus estimating pixel-level yields. Because previous work generated yield maps through 2018, we used Google Earth Engine (Gorelick et al., 2017) to extend estimates to years 2019 and 2020 based on Landsat satellite data using the maize methodology described in Deines et al. (2021) and the soybean methodology described in Dado et al. (2020).

The accuracy of these remotely-sensed, sub-field scale yield maps is a key element to understand when making inferences about management impacts. Because these datasets were trained and validated on over one million ground truth fields for each crop spanning the full

Corn Belt for 2008-2018, they are better evaluated than any other satellite yield dataset to date, particularly at high-resolutions (e.g., pixel-scale) rather than aggregated mean yields (e.g., counties in the US). At the pixel level, these approaches capture 40% and 27% percent of pixel-level yield variation in maize and soybeans, respectively (and 69% and 63% of county-aggregated yields). While these satellite yield estimates have noise, as long as this error is random and uncorrelated with the treatment variable, it can still be used for inference; the noise may, however, lead to attenuation bias and underestimate effects (Jain, 2020). Additionally, the ground data itself – combine harvesters with onboard yield monitors - has some noise, which can lead to an underestimation of model performance (Burke, Driscoll, Lobell, & Ermon, 2021). Along with direct accuracy comparison with ground truth, accuracy can also be judged by how well the dataset can reproduce inferred responses to external variables, particularly those not in the model (Burke et al., 2021; Burke & Lobell, 2017; Lobell et al., 2019). For example, SCYM maize estimates and ground yield data both displayed similar responses to management and environmental variation not included in the SCYM model, including linear and nonlinear responses (Deines et al., 2021). A full set of validation plots and metrics can be found in the source publications (Dado et al., 2020; Deines et al., 2021).

We acquired environmental and weather data from available gridded datasets for the study region to describe annually varying weather as well as static field properties (Figure 3). Static properties included 1981-2010 climate normals from PRISM (Daly et al., 2008; Daly, Smith, & Olson, 2015), field slope derived from the National Elevation Dataset (USGS, 2012), and soil variables from the gSSURGO soil database (NRCS, 2016). Specific soil variables of interest can be found in gSSURGO’s Value Added Look Up Table (Valu1) of derived soil attributes and included the soil productivity indices for corn and for soybean (known as the National Commodity Crop Productivity Index, or NCCPI), root zone available water content, and soil drainage class. Annual monthly and seasonal summaries of temperature and precipitation were extracted from the GRIDMET climate reanalysis product at 4 km resolution (Abatzoglou, 2013). Monthly estimates of soil moisture and climate water deficit for the growing season were obtained from the TerraClimate dataset, also at 4 km resolution (Abatzoglou, Dobrowski, Parks, & Hegewisch, 2018). The full set of environmental covariates, their temporal aggregation period, and their data sources are provided in Table S1. Subsets of covariates selected for use during model development and analysis are listed in Tables 1 and 2.

2.3 Sampling approach

Here, we defined the treatment as pixels which were classified as cover cropped for the sampling year of interest (2019 or 2020) and had a history of being cover cropped at least 3 times between 2015-2020 based on the satellite-derived cover crop map dataset (Fig. 3). We included cover cropping history to guard against spurious classifications in the satellite dataset and to allow for some accumulation of soil benefits from cover cropping. Because cover cropping is relatively rare on the landscape (~5% of agricultural area in the study region), we designed an exhaustive sampling technique to generate one random sample point for all cover cropped field entities in the map dataset. As we lack dynamic field boundaries that reflect year-to-year changes in cropping and management practices like cover cropping, we defined these “field entities” as contiguous groups of pixels at least 5 ha in size with the same cover crop history for 2015-2020. We then randomly sampled 1 point location from each field entity. This resulted in 10,877 unique sample locations for maize and 11,827 unique locations for soybeans across the study region (Figs. 3,4).

For control locations, we first isolated all pixels in the 6-state study region which were never classified as "cover cropped" in the map dataset between 2000-2020. We then generated a random point dataset across the full region designed to balance sample locations in space and provide ample control locations to better ensure good overlap in covariate space with the treatment locations (see section 2.4). After generating a uniform 50 km^2 grid over the study region, we randomly sampled 150 points per grid cell over locations which were either maize or soybean in both 2019 and 2020, with crop type assigned from the USDA NASS Cropland Data Layer (Boryan, Yang, Mueller, & Craig, 2011). We note that the purpose of the sampling grid was to ensure a spatially even sampling density; grid location was not considered when weighting control samples based on covariate similarity to treatment samples (see section 2.4). This resulted in 40,010 maize and 35,334 soybean control point samples across the study region (Fig. 4). For each sampling point, we then extracted the crop type, remotely sensed yield, soil and slope information, and weather covariates for both 2019 and 2020. The compiled point dataset can be accessed at https://doi.org/10.5281/zenodo.7199708. To balance open data with farmer data privacy (Zipper et al., 2019), location information is provided at the county-level only (latitude and longitude coordinates have been removed).

2.4 Causal forests analysis

Our study uses observational satellite datasets of cover cropping and yields. Unlike in randomized control experiments, treatment status in observational studies cannot be assigned at random. This presents a challenge for identifying causal effects, since treatment status is likely correlated with other factors that also influence the outcome. These factors may be observed or unobserved and can confound an observational analysis if not accounted for (Athey & Imbens, 2017). In our application, farmers might implement cover cropping on lower- or higher-yielding fields, making it difficult to assess how cover cropping itself affects crop yields. Here, we address this challenge by using causal forests, a machine learning approach designed to estimate treatment effects in observational data (Athey, Tibshirani, & Wager, 2019).

Causal forests are a recent adaptation of the classic random forests algorithm, which generates consensus predictions from many individual classification or regression trees (Breiman, 2001). Broadly, causal forests estimate treatment effects by comparing outcomes for each treatment sample against available control samples which are weighted based on their similarity to the treatment sample. In this way, they act as an adaptive kernel method well-suited to cases with heterogeneity in treatment effects (Athey et al., 2019; Wager & Athey, 2018). In other words, for our study, causal forests allow us to use each field's closest neighbors in covariate space to generate a counterfactual yield estimate under the alternative management practice. Further, causal forests guard against confoundedness, including by unobserved variables, by using a "doubly robust" treatment estimation method that combines treatment propensity weighting (Rosenbaum & Rubin, 1983) – in our case, how likely a field is to be cover cropped - and regression adjustment based on a model specifying the expected outcome – in our case, a yield model. This doubly robust method is referred to as augmented inverse-propensity weighted estimation (Robins & Rotnitzky, 1995), and minimizes sensitivity to misspecification in either model (Athey et al., 2019; Scharfstein, Rotnitzky, & Robins, 1999).

Causal forests generate mathematically valid confidence intervals and, as a random forests method, are robust to large numbers of covariates, nonlinear interactions, and overfitting without requiring explicit model specification (Athey & Imbens, 2016; Athey et al., 2019; Belgiu & Drăgu, 2016; Wager & Athey, 2018). Recent studies have found causal forests are better able to detect and quantify heterogeneous treatment effects than conventional econometric methods (Baiardi & Naghi, 2021; Farbmacher, Kogel, & Spindler, 2019; Strittmatter, 2019).

Recent work has applied causals forests to satellite data in the US Corn Belt to understand the yield impacts from conservation tillage (Deines, Wang, & Lobell, 2019) and crop rotations (Kluger, Owen, & Lobell, 2022). In the latter study, causal forests estimates of yield impacts using satellite-derived yields and crop type maps had a statistically significant positive correlation with estimates from experimental field sites, although they did tend to underestimate the treatment effect in this case.

Here, we used the 'grf' package (Tibshirani et al., 2018) in R (R Core Team, 2014) to run a separate causal forests analysis for maize and soybeans. We designated cover cropping as the treatment variable and log yield as the outcome. We used log yields to allow for the magnitude of yield impacts to be multiplicative; results were similar for models using absolute yield values. The causal forests algorithm includes two model subroutines to model the likelihood of treatment (propensity model) and the expected outcome (yield model) used in the doubly robust treatment estimation. We first used the full set of static covariates, including soil properties and climate normals, to estimate treatment propensity using 2000 trees and default function settings. To account for spatial factors in adoption, we also included latitude and longitude as covariates. The full set of variables used are listed in Tables 1 (maize) and 2 (soybeans) in order of variable importance within each sub-model, with importance defined as the number of times each variable was used to split the individual trees. To ensure control observations provided suitable neighbors for treatment observations in covariate space and meet causal forests' assumption of overlap (Athey et al., 2019), we removed observations with propensity scores below 0.05 (samples which were unlikely to be treated based on the propensity model). No samples had a propensity score higher than 0.95, so there was no need to filter samples with very high treatment likelihoods. This resulted in a final sample size of 45,595 for maize and 44,235 for soybeans.

For the yield outcome sub-model, we selected crop-specific variable sets by using multivariate adaptive regression splines (MARS) models (Friedman, 1991) as implemented in the "earth" R package (Milborrow, 2019) with the full set of annual weather covariates and soil and slope properties. MARS selected variables, along with a year term, were then used in the causal forests routine to model expected outcomes, again with 2000 trees and default parameters. Selected variables and their relative importance can be found in Tables 1 and 2 for maize and soybeans, respectively.

Finally, we used the variables selected for the outcome model and all soil properties to estimate the treatment effects of cover cropping using the `causal_forest` function in grf with 2000 trees and default parameters. We converted treatment effects from log yield to percent yield for interpretation. Results are reported as the main effect with a 95% confidence interval, with the latter estimated within the 'grf' package by fitting groups of trees on subsets of the data and examining variance of predictions across these groups (Tibshirani et al. 2018). This confidence interval is a measure of the statistical bounds of the estimated treatment effect, given the data. All else being equal, noisier input data will result in wider confidence intervals.

We then tested for heterogeneous treatment effects using the `test_calibration` function in grf and, finding statistically significant heterogeneity, we examined covariates associated with high and low yield impacts using Principal Components Analysis on the six most important covariates in the treatment effects model for each crop (Tables 1 and 2). To map treatment effects in space, the conditional average treatment effects (CATE) for each observation were averaged on a 5 km^2 grid across the region.

2.5 Robustness check for causal forests analysis

Using the maize causal forests model, we ran a placebo test in which we replaced 2019-2020 yields with the mean yield for each sample between 2000-2010, based on the same SCYM satellite dataset. This test helps us address two potential weaknesses in our method: 1) that there is one or more unobserved variables which strongly influence field selection into the cover cropping treatment that is not captured by our suite of soil and weather variables, nor mitigated by the doubly-robust properties of the causal forests framework; and 2) that there is some error in treatment assignment based on the remotely-sensed cover crop map datasets. Because cover cropping has only expanded in recent years, we assume the treatment status for this placebo test to be unrelated to yield outcomes. Thus, we would expect to find no treatment effect if farmers were not preferentially selecting lower or higher yield fields into cover cropping. Similarly, if the treatment status assignment was not meaningful for the main statistical analysis, we might expect to find a similar treatment effect in this placebo test.

3. Results

The causal forest results indicated that fields where cover crops were adopted for three or more years experienced an average maize yield loss of 5.5% (95% confidence interval (CI): 5.1% – 5.9%) in the study region, compared to fields that did not practice cover cropping. Nearly all locations appeared to experience negative effects, with only 0.6% of observations estimated to have a positive CATE (treatment effect conditioned on that observation's properties). In general, impacts appeared most negative in Iowa and Northern Illinois compared to the rest of the study region (Fig. 5). These areas were generally associated with better soil ratings, higher mid-season temperatures, and lower amounts of April rainfall for the two years in which yield outcomes were considered (2019 and 2020) (Table 1, Fig. 6).

For soybean, we also estimated negative impacts of cover crops on soybean yields, although the effects were smaller. On average, soybean yields were reduced by 3.5% (95% CI: 3.2% - 3.9 %) following cover crop adoption, with 2.6% of CATEs having a positive value (Fig. 7). Also similar to maize, the most negative impacts were observed for soybean on the better soils (i.e. those with higher NCCPI soil productivity ratings), although these effects were more muted than for maize (Table 2, Fig. 8). Average daytime temperature and vapor pressure deficit in June were also important sources of heterogeneity for soybean, with fields that experienced warmer Junes exhibiting the most negative outcomes. Lower amounts of early (April) and late-season (August) precipitation also were associated with larger yield losses (Table 2, Fig. 8).

The results were robust to using yield levels rather than log yields as the response variable. For maize, the mean effect when using levels was a yield loss of 5.2% compared to 5.5% for logs, while for soybean the mean effect was 3.5% for both. The spatial patterns and interaction with covariates were also very similar for the two approaches. For the placebo test based on mean 2000-2010 maize yields, the estimated treatment effect was not significantly different from zero (ATE = -0.4%; 95% CI: -0.9% - 0.1%). The mean effect size in the placebo test was an order of magnitude smaller than the main test using the observed 2019-2020 yields (0.4% vs 5.5% reduction). This null effect lends strength to the causal forests methodology for guarding against bias from selection on unobserved variables.

4. Discussion

Our estimated mean yield loss of 5.5% for maize is consistent with results from experimental and modeling studies, especially when considering that the predominant species used for cover cropping in the study region have been non-legumes such as cereal rye and annual ryegrass (Wallander et al., 2021). For example, a global meta-analysis reported an average yield loss of 4% across studies with various combinations of primary and cover crop species (Abdalla et al., 2019), finding that non-legume cover crops generally resulted in greater yield losses. The simulation study of Qin et al. (2021) predicted a 3.9% yield loss in Illinois for maize following annual ryegrass in Illinois.

Comparison of soybean results with previous studies is more difficult because of the relative lack of experiments using a legume as the primary crop. For instance, none of the 154 yield comparisons performed in Abdalla et al. (2019) included soybean as the primary crop. In soybean experiments in Argentina, Alvarez et al. (2017) reported ~2% yield losses following cover crops, which were smaller in magnitude but not statistically distinguishable from the yield losses for maize following non-legume cover crops. Qin et al. (2021) reported no significant differences in simulated soybean yields with and without cover crops, although the relatively small number of simulations led to wide confidence intervals.

In addition to providing an estimate of the magnitude of yield impacts in farmers' fields, our results provide some potentially useful clues about the mechanisms behind the yield impacts. One well-known mechanism from prior work relates to nitrogen (N) dynamics. Non-legume cover crops immobilize a substantial fraction of soil N – indeed this is one of their primary benefits with regards to reducing N losses – and the release of N after termination is often too slow to avoid some N stress for the primary crop in the current year. Thus, experiments and simulations tend to show larger impacts on fields with fewer fertilizer inputs (Abdalla et al., 2019; Qin et al., 2021). In our case, although we did not have fertilizer rate information for the commercial fields in this study, we point towards two features that are consistent with the importance of N dynamics. First, we found greater yield losses for maize than soybean, which likely reflects soybean's lower need for fertilizer N. Second, we found that maize yield impacts were significantly more negative on fields with a high soil productivity index (NCCPI). Since these fields have higher yield potential, they accordingly have higher N needs to meet their yield potential. That is, immobilization of N is more likely to affect the crop when other yield constraints are less binding.

A second mechanism highlighted in modeling work is that cover crops can compete for water, and in particular maize yield losses can be exacerbated when cover crops are used prior to dry growing seasons. Indeed, our results indicate that April precipitation was an important determinant of maize yield loss, with the most negative yield impacts observed in the locations and years with less rainfall (Fig. 6). Similarly, a recent meta-analysis of dryland systems found that cover crops reduced soil water content by 18% at planting on average, and that cover crops may impact yields when annual precipitation is below 700 mm (Garba, Bell, & Williams, 2022). However, these effects may be at least partially counteracted on longer time horizons by positive changes in soil physical properties such as water holding capacity, though changing soil physical properties by cover crop usually takes a long time to realize. One study examining fields in central Iowa with 13 year winter rye cover crop history found cover crops led to significant ~10% and ~20% increases in soil water field capacity and plant available water, respectively, and did not show significant yield differences compared to control fields (Basche et al., 2016). This suggests subsidies for cover cropping could be focused on years following adoption and reduced over time.

A third potential mechanism relates to potential O_2 depletion in the soil during the early growing season, especially during wet springs (e.g., existing O_2 stress may be exacerbated by cover crops due to the further consumption of O_2), whereby the activity of soil microbes stimulated by the cover crop consumes O_2 to the point of stressing the primary crop. Prior modeling work has shown that O_2 stress can be a non-trivial component of yield loss in maize following a cover crop (Qin et al. 2021). This mechanism is difficult to disentangle from the effects of water stress since additional water tends to enhance microbial activity and exacerbate O_2 depletion while at the same time alleviating water stress. Nonetheless, we find some limited evidence for this mechanism, particularly in soybean, where higher temperatures in June are associated with greater yield penalties. However, these patterns could also be explained by greater weed competition for soybean in these conditions, especially if termination of the cover crop is not complete. With spring in the US Midwest may experience wetter conditions (Li, Guan, Schnitkey, Delucia, & Peng, 2019; Prein et al., 2017), fully understanding this factor becomes more critical.

The negative yield impacts reported here represent an important downside to the rapidly expanding use of cover crops. At current prices (roughly $197 per metric ton ($5 per bushel) of maize and $441 per metric ton ($12 per bushel) of soybean), a 5% loss of maize grain yield or 3% loss of soybean yield would represent roughly $100 and $50 per hectare, respectively, in foregone revenue ($40 and $20 per acre). When added to the cost of implementing cover crops and technical overhead (Roesch-Mcnally et al., 2018), recently estimated to have a median cost of $99 per hectare but with large variability (Bowman, Poley, & McFarland, 2022), this represents a formidable obstacle to long-term adoption of the practice.

Negative yield impacts could also counteract come of the public benefits of cover cropping, since productivity declines undoubtedly lead to substantial indirect environmental costs associated with other lands having to make up the shortfall in production. That is, negative effects on total factor productivity in the study region would contribute to the expansion of cultivated land area both within and outside of the U.S. (Villoria, 2019), with associated impacts on carbon and N cycles. A full exploration of the tradeoffs associated with the indirect impacts of yield declines is left to future work.

Optimistically, it is possible the currently negative yield impacts could be mitigated with improved management practices, such as choice of cover crop species and the timing of termination prior to planting. While subsidy programs increase financial support to farmers for adopting cover crops, technical assistance is also warranted and may be equally important to realize the promise of cover crops.

5. Conclusions

By combining satellite-based datasets on recent cover cropping adoption and yields of maize and soybeans, this study provides robust identification of the effect of cover cropping on subsequent yields of primary crops in the United States. We observe clear negative impacts on yields and identify the conditions under which these yield penalties are most severe. Our approach provides a large sample of real-world, commercial scale fields, enabling us to detect a statistically significant, though relatively small yield effect among background yield variability due to weather, soils, cultivars, and management. This effect would be difficult to estimate with limited sampled sizes from more time-intensive sampling techniques such as crop cuts. By demonstrating an ability to track these effects, this method could be used as a low-cost approach for ongoing understanding of implementation successes and challenges.

Overall, we consider this work to have two important implications relevant to agricultural policy makers. First, the presence of significant yield penalties should motivate efforts to encourage implementation of practices that are known to minimize these penalties. Specifically, most farmers practicing cover cropping currently use rye as the cover crop (Wallander et al., 2021), whereas alternatives such as clover, hairy vetch or other legumes would likely result in higher primary crop yields. Ensuring that the cover crop is terminated with enough lead time before planting primary crops can also reduce the likelihood of significant yield penalties (Marcillo & Miguez, 2017; Qin et al., 2021).

Second, given the large heterogeneity of yield penalties, policy makers could encourage adoption of cover cropping more strongly in areas that are least likely to experience significant penalties. For example, areas with poorer soils and with less susceptibility to water stress appear to experience the smallest yield losses in our study. In many cases, these more humid areas with less productive soils may also represent the areas where benefits in terms of reduced N losses and improved soil carbon are likely to be greatest. We anticipate that public payments for cover cropping will evolve to be a more targeted program that emphasizes areas with the largest public benefits and least public costs, just as the USDA Conservation Reserve Program currently prioritizes parts of farmers' land that are considered environmentally sensitive. The yield impacts of cover cropping should be an important factor in defining these benefits and costs.

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Data Availability Statement

Data supporting the analyses and R code for the analyses and figure generation are available on Zenodo at https://doi.org/10.5281/zenodo.7199708. This includes the sample points extracted from the cover crop map dataset and their related yield, soil, and weather attributes. Due to privacy concerns, the latitude and longitude for each sample point have been removed and location information is available at the county level only. Similarly, the yield map datasets are not publicly available but interested users may contact David Lobell to arrange a formal data sharing agreement for non-commercial research purposes. The cover crop map datasets are not publicly available but interested users can contact Kaiyu Guan for potential use agreement.

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Tables

Table 1. Variables used in the causal forests analysis for maize samples. Variables are listed in order of their relative importance based on the number of splits. VPD = vapor pressure deficit; precip = precipitation; temp = temperature; PAWS = plant available water storage.

Treatment Propensity (30 yr Climate Normals)	Expected Yield Outcome	Treatment Effect
Longitude	Soil suitability index	Soil suitability index
May precip	July VPD	July max temp
July VPD	Aridity (June - August)	April precip
Latitude	Soil PAWS	Solar radiation (June-August)
June Precip	June precip	April soil moisture
July Precip	April soil moisture	July VPD
April mean temp	April max temp	June Precip
June VPD	June max temp	Aridity (June - August)
May mean temp	August max temp	Soil PAWS
August mean temp	July precip	April max temp
June mean temp	July max temp	May mean temp
July mean temp	June VPD	August max temp
Slope	May mean temp	Slope
Soil drainage class	Year	Drainage class
April precip	Solar radiation (June - Aug)	July precip
Soil PAWS	May - Aug precip	May - Aug precip
Soil suitability index	Soil drainage class	June - August mean temp
	June - August mean temp	June VPD
		June max temp
		Year

Table 2. Variables used in the causal forests analysis for soybean samples. Variables are listed in order of their relative importance based on the number of splits. VPD = vapor pressure deficit; precip = precipitation; temp = temperature; PAWS = plant available water storage.

Treatment Propensity (30 yr Climate Normals)	Expected Yield Outcome	Treatment Effect
Longitude	June max temp	June max temp
Latitude	Soil PAWS	June VPD
June VPD	August max temp	August precip
May mean temp	August precip	Soil PAWS
June mean temp	Year	Soil suitability index
July mean temp	April soil moisture	April precip
August mean temp	Soil suitability index	Aridity (June - August)
April mean temp	July VPD	July VPD
June precip	April precip	May soil moisture
July precip	May soil moisture	April soil moisture
May precip	April max temp	July precip
April precip	June VDP	August max temp
Soil drainage class	May mean temp	July max temp
Slope	April mean temp	Slope
July VPD	May min temp	May precip
Soil PAWS	Aridity (June - August)	April max temp
Soil suitability index	July max temp	May mean temp
	July precip	May min temp
	May precip	April mean temp
		Soil drainage class
		Year

Figures

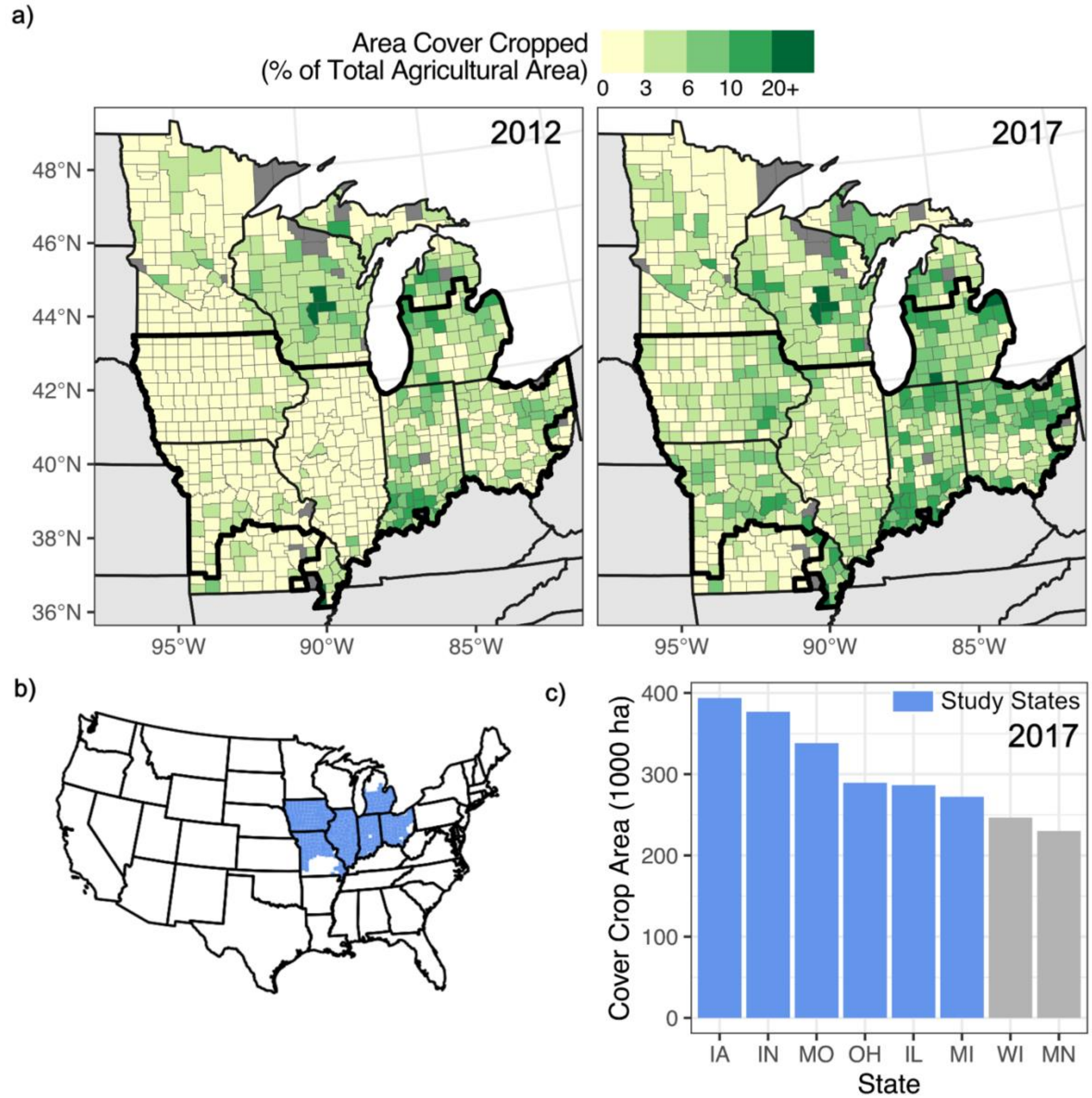

Figure 1: Study area and cover crop prevalence. a) Cover cropping prevalence in the US Corn Belt by county in 2012 and 2017, shown as a percentage of total agricultural area. Study area boundary is outlined in bold. b) Study area location within the United States. Counties with available cover crop maps are shown in blue. c) Total cover crop area per state in the most recent Agricultural Census, with the six states in this study highlighted in blue. Data for panels (a) and (c) are from the 2012 and 2017 Agricultural Census (NASS, 2021).

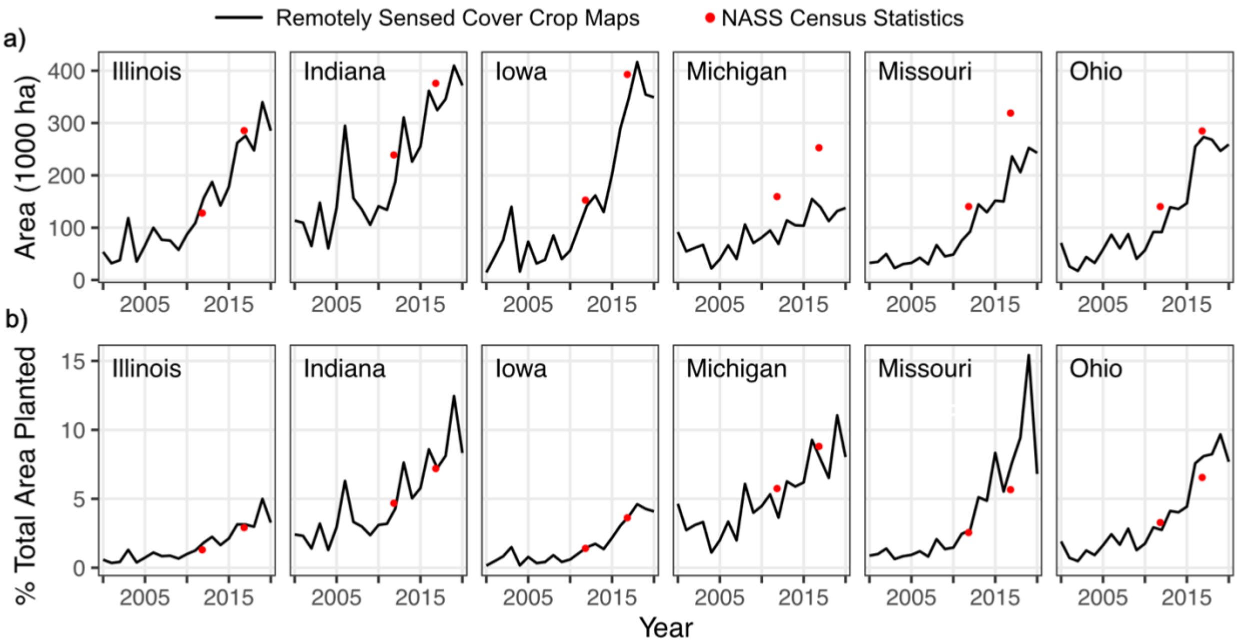

Figure 2: Cover crop trends over time. Solid line depicts annual state-aggregated cover crop area between 2000-2020, based on counties in the cover crop map dataset (Fig. 1). a) Annual cover crop by absolute area. b) Annual cover crop by percent of total agricultural area planted from the USDA National Agricultural Statistics Service (NASS) annual surveys. Red dots show NASS Agricultural Census estimates of cover cropping for 2012 and 2017 for comparison.

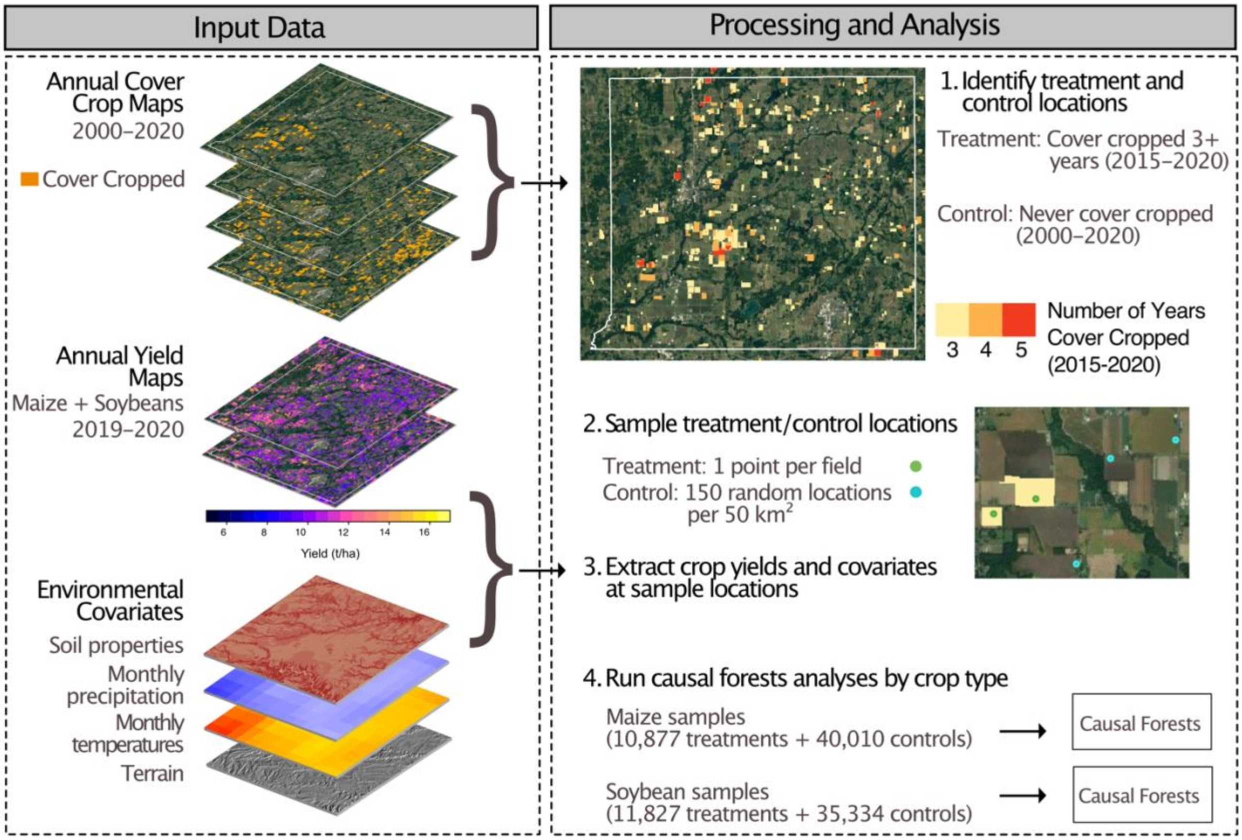

Figure 3: Workflow overview. Cover crop and yield data are shown for St. Joseph County, Michigan (white outline).

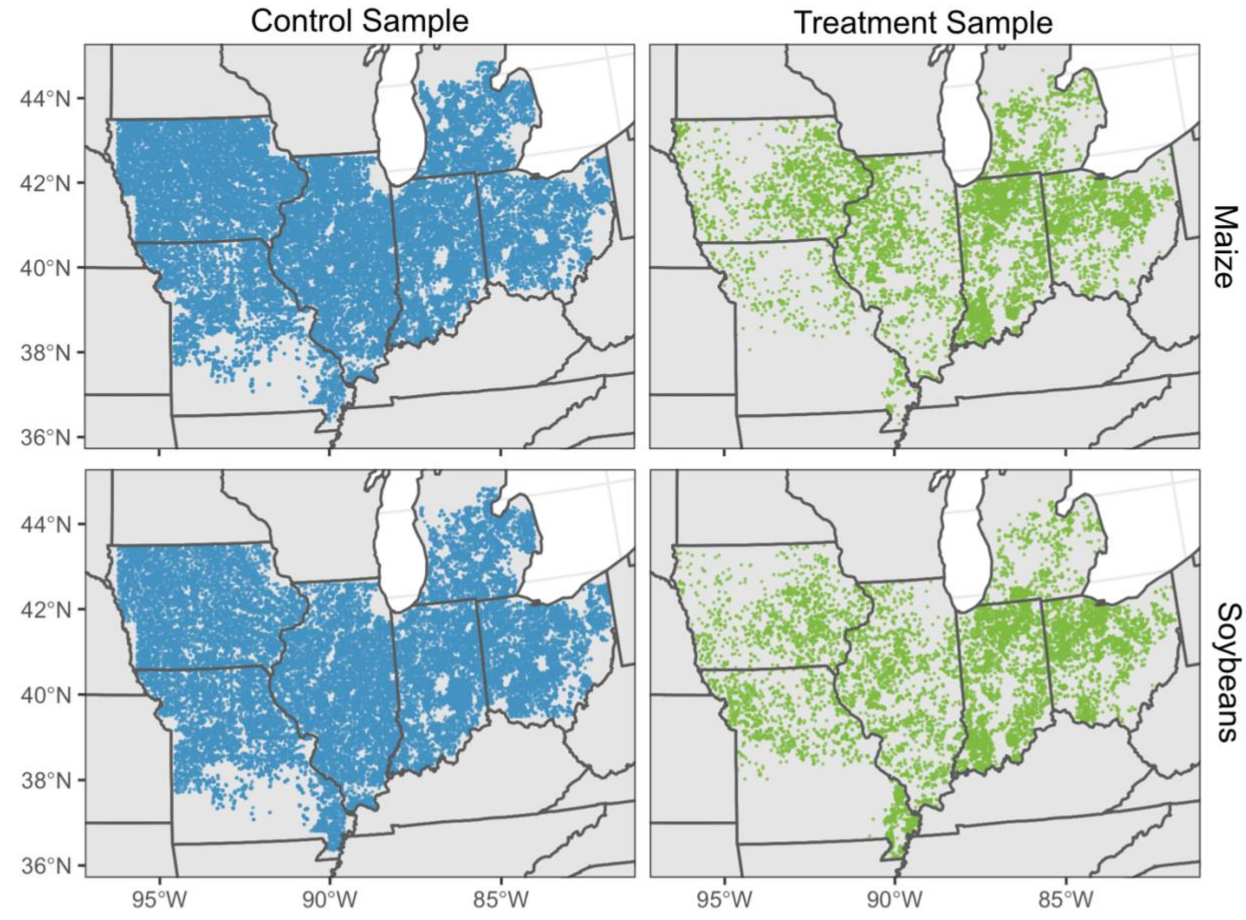

Figure 4: Locations of treatment and control point samples for maize and soybeans.

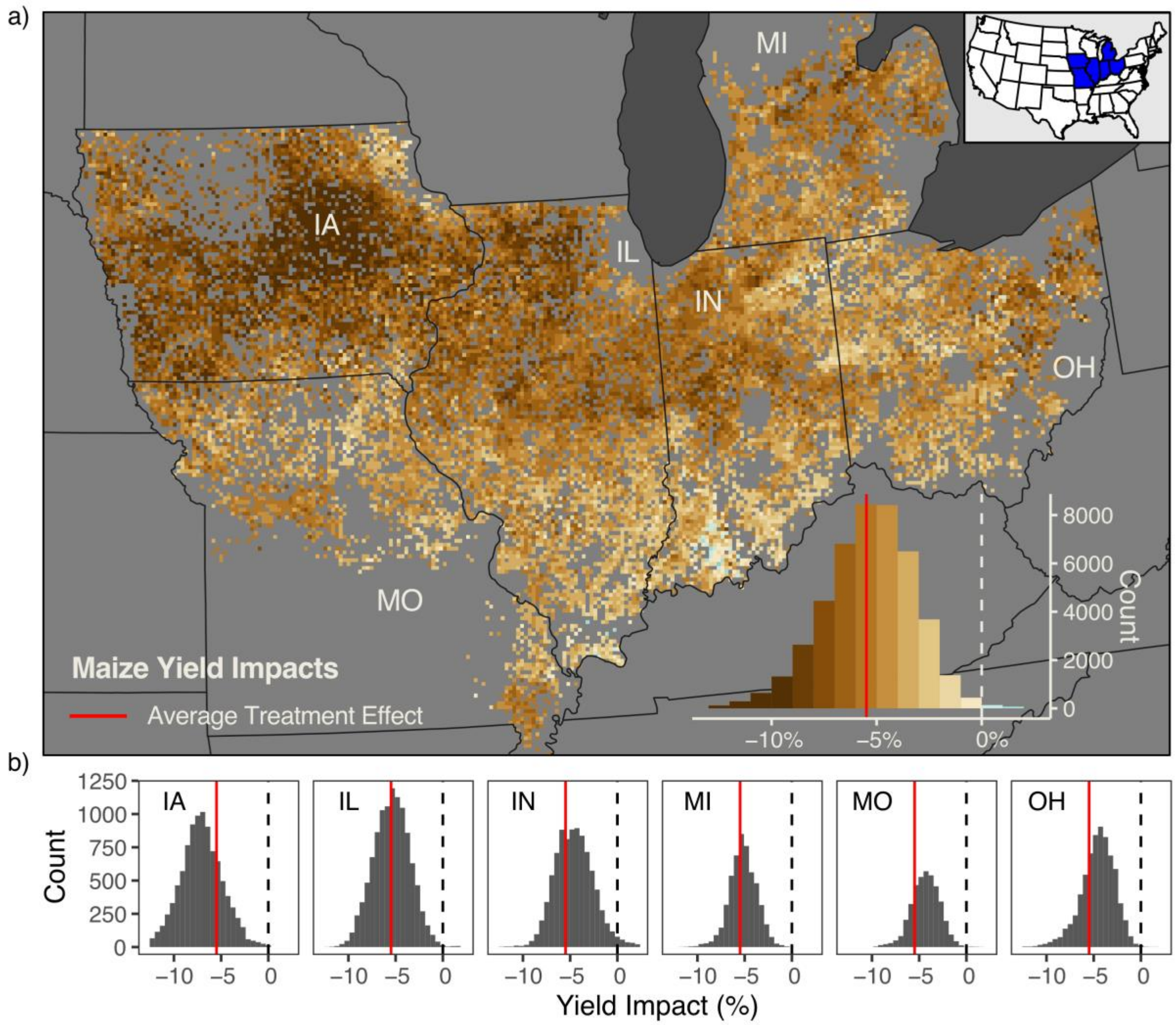

Figure 5: Distributions of maize yield impacts from cover cropping in 2019-2020. a) Mean conditional treatment effects by aggregating all samples on a regular 5 km^2 grid. The histogram scales provide the distribution of treatment effects across all samples. b) Distribution of treatment effects by state. For all plots, the red line indicates the average treatment effect for the entire region.

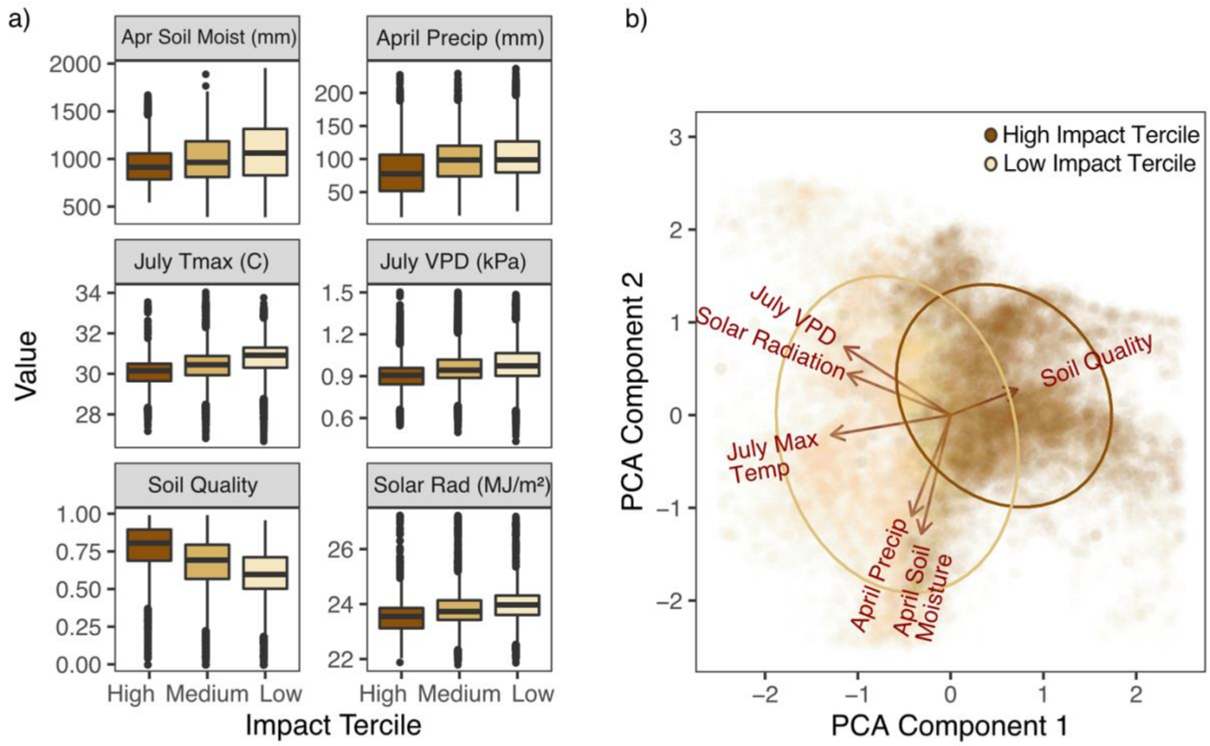

Figure 6: Heterogeneous treatment effects by environmental covariates for maize. a) Covariate distributions by treatment effect group. b) Principal components analysis for the low and high impact terciles. Vectors indicate the strength of each covariates' contribution to axis separation. All: Treatment groups are defined based on terciles from all samples, with the "high impact tercile" representing samples with the most negative yield impacts and the "low impact tercile" representing samples with the least (and occasionally positive) yield impacts. Covariates examined represent the six most important variables in the causal forests estimates of treatment effects.

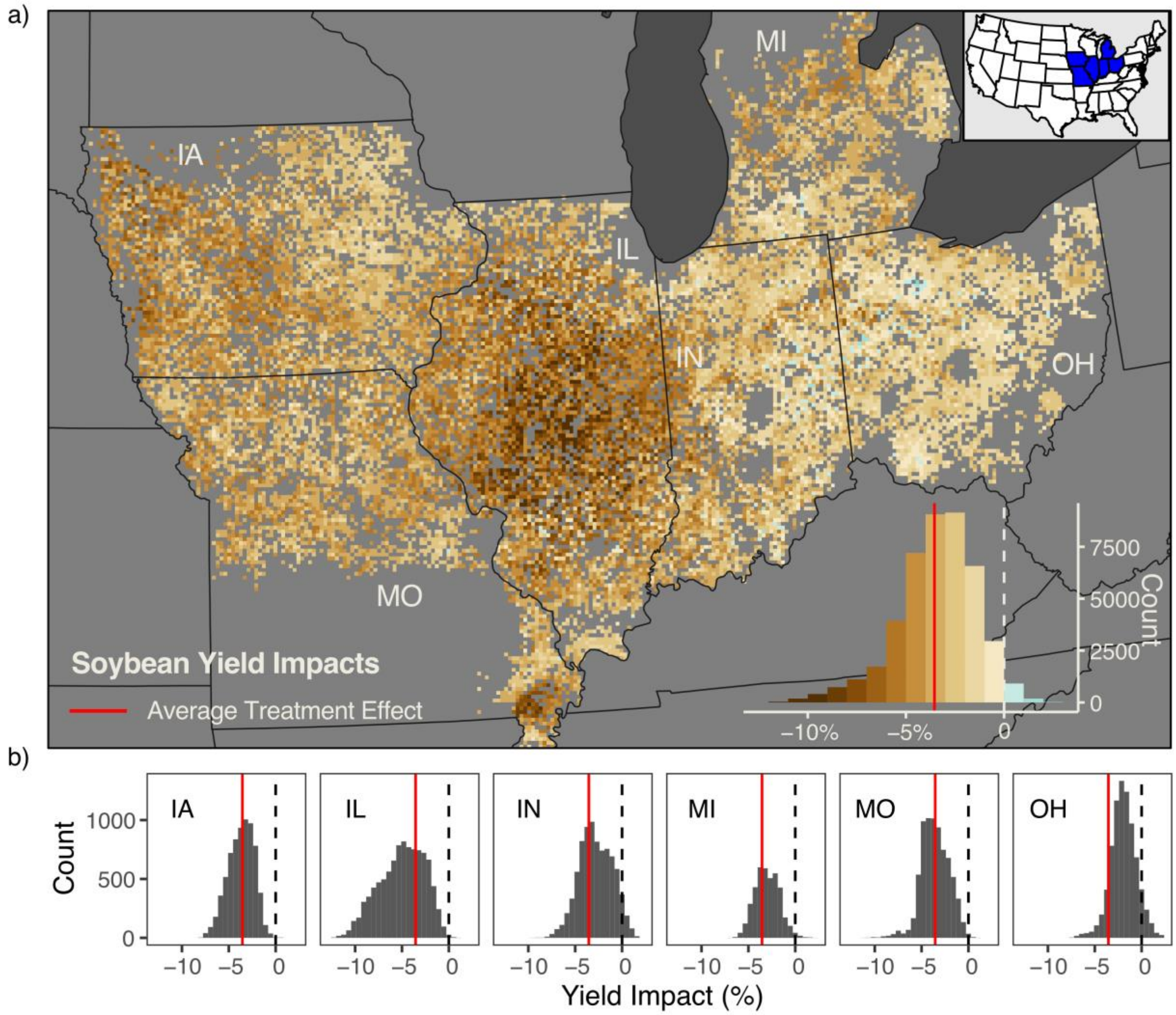

Figure 7: Distributions of soybean yield impacts from cover cropping in 2019-2020. a) Mean conditional treatment effects by aggregating all samples on a regular 5 km^2 grid. The histogram scales provide the distribution of treatment effects across all samples. b) Distribution of treatment effects by state. For all plots, the red line indicates the average treatment effect for the entire region.

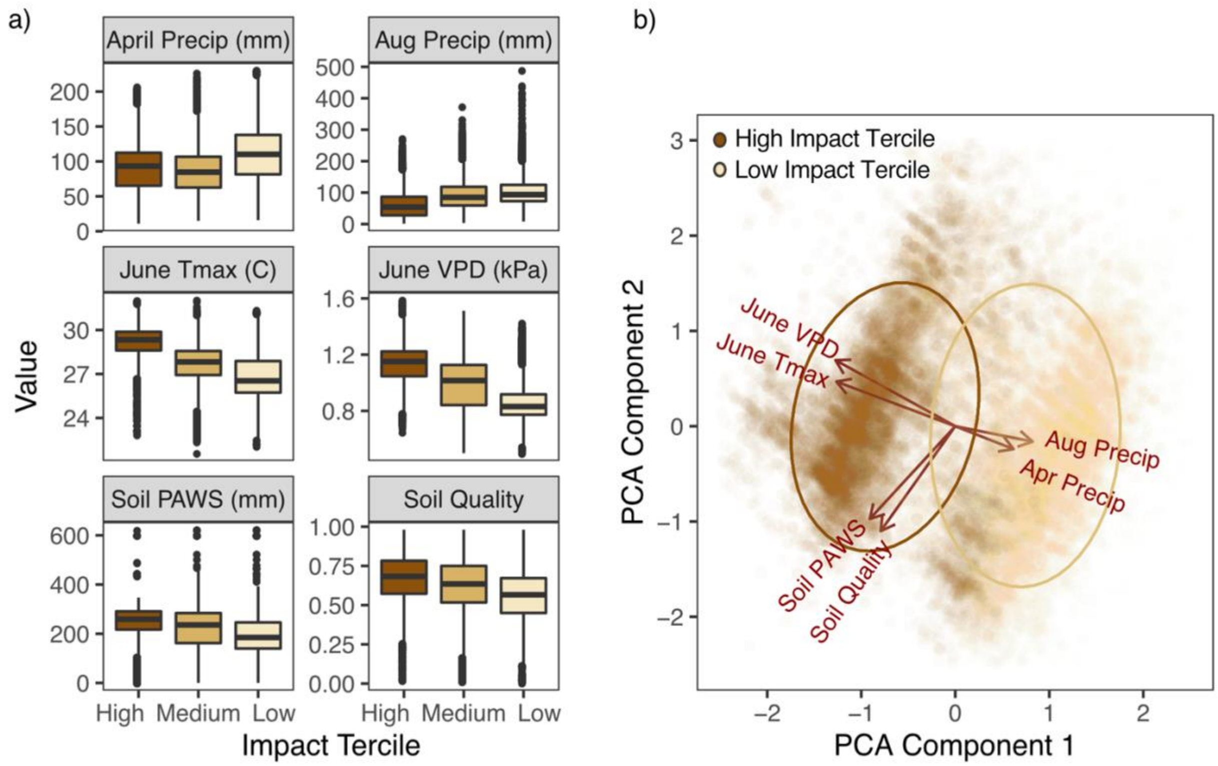

Figure 8: Heterogeneous treatment effects by environmental covariates for soybeans. a) Covariate distributions by treatment effect group. b) Principal components analysis for the low and high impact terciles. Vectors indicate the strength of each covariates' contribution to axis separation. All: Treatment groups are defined based on terciles from all samples, with the "high impact tercile" representing samples with the most negative yield impacts and the "low impact tercile" representing samples with the least (and occasionally positive) yield impacts. Covariates examined represent the six most important variables in the causal forests estimates of treatment effects.