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Further adoption of conservation tillage can increase maize yields in the western US Corn Belt

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Abstract

Conservation tillage can reduce soil erosion, increase soil health, and decrease labor and fuel input costs. Despite these benefits, potential yield impacts remain an important concern for farmers considering adoption. Previous research suggests that conservation tillage is likely to have the largest yield benefits in more arid conditions, but a lack of field-level analyses across climatic, management and soil conditions limits confidence in such predictions. Satellite imagery provides the opportunity to monitor agricultural lands at sub-field resolution across large spatial scales and wide environmental gradients. Here we investigate the maize yield impacts of conservation tillage in the semi-arid western US Corn Belt, using sub-field resolution datasets on tillage practices and crop yields derived from satellite data spanning four states (Nebraska, Kansas, South Dakota, and North Dakota) between 2008 and 2020. On these datasets, we estimate heterogenous yield outcomes for several thousand maize fields across gradients in climate, soil quality and irrigation status by using a causal forests analysis, an adaptation of the random forests machine-learning algorithm for causal inference on observational data. We find that long-term adoption of conservation tillage increased rainfed maize yields by an average of 9.9% in the region. Impacts on irrigated yields were small and not statistically significant. These results, along with an analysis of variables related to greater than average yield benefits, indicate that improved water infiltration and retention are the primary reasons for conservation tillage benefits. Despite yield benefits, many fields estimated to see increased yields under long term low till have not adopted the practice. Therefore, we identify specific counties likely to benefit most from increased levels of adoption. Our results strengthen the understanding of the impacts of conservation agriculture on crop yields and help define environments and counties most likely to benefit from conservation tillage.

1. Introduction

Globally, conventional high-intensity tillage (hereafter, high till) practices are being reexamined due to land degradation resulting from methods that highly disturb soil. Worldwide, approximately 35 billion tons of agricultural soils per year are lost through erosion, with especially high rates in the developing world (Borrielli *et al* 2017). Tillage erosion drives soil loss in the Midwestern US, with over a third of the region having lost highly organic A-horizon soil, resulting in an estimated impact of 1.8–3.7 billion dollars in economic losses every year (Thaler *et al* 2021). In response, the practice of low intensity

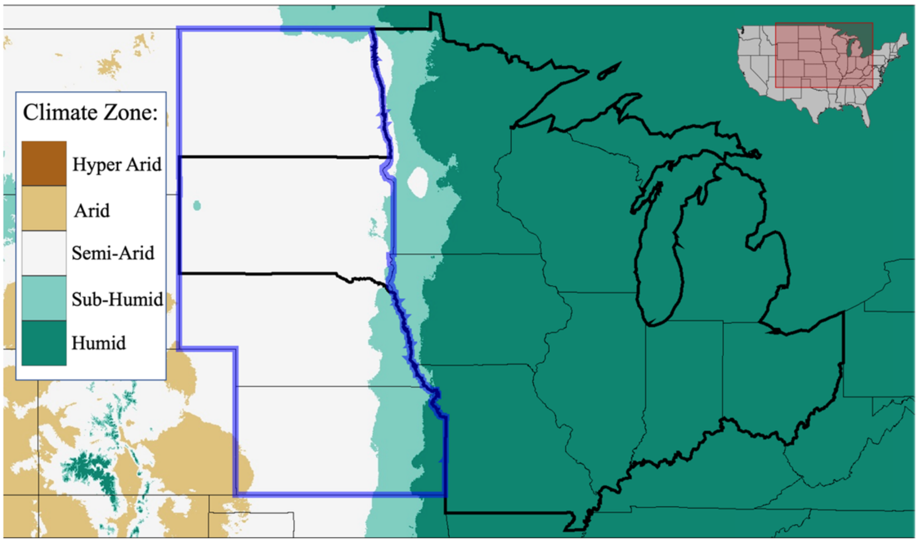

Figure 1. Map of the study area. The study area for this paper is the 4-state western Corn Belt outlined in blue, which extends previous work (Deines *et al* 2019a) focused on 9 central Corn Belt states (bold black outline). Climate zones are from (Trabucco and Zomer 2019).

conservation tillage (hereafter, low till) has emerged. Commonly defined as leaving at least 30% of the soil surface covered in organic matter, low till in this study refers to the separate practices of no-till, reduced-till strip tillage, mulch tillage, row till and contour till. Low till methods decrease labor and fuel costs (Weersink *et al* 1992), improve soil health, and benefit soil biota (Kuntz *et al* 2013). However, concerns about potential adverse yield impacts can inhibit adoption (Kurkalova *et al* 2006).

To date, studies examining the yield impacts of tillage type have found mixed results, often due to differences in water availability. A global meta-analysis of 678 field studies found that no till reduced maize yields by 7.6% overall, but yields were similar or higher in arid environments (Pittelkow *et al* 2015b). A meta-analysis of global semi-arid and sub-humid environments found that yields under low till regimes depended on soil texture, with loam and sandy soils generally experiencing yield benefits due to soil texture impacting drainage and thus water availability (Rusinamhodzi *et al* 2011). A 20 year study in Italy found that fields with adequate water availability had higher yields with high intensity methods, while no-till led to greater yields when crops were under high water stress (Ruisi *et al* 2014). These studies indicate that low till can be relatively more beneficial in dry rather than humid conditions, though the absolute yield effects remain hard to predict for any given cropping system.

Remote sensing approaches can complement field-based studies by enabling comparisons across thousands of fields over broad spatiotemporal, biophysical, and management practice distributions, providing insights into the effects on yield of tillage practices as they are implemented on the landscape (Derpsch *et al* 2014, Mutanga and Kumar 2019, Deines *et al* 2019a). Previous work using remote sensing in the humid central US Corn Belt found small maize yield increases (∼3%) associated with long-term low till, with higher increases in more arid locations and years (Deines *et al* 2019a). Here, we build on these results by focusing on the western Corn Belt states of Kansas, Nebraska, North Dakota, and South Dakota, which have a semi-arid climate and for which there has been no large-scale analysis (figure 1). The area is of particular interest due to projected increases in water stress in the Corn Belt over the next century (Bhattarai *et al* 2017, Ting *et al* 2021). Therefore, understanding the effects of low till in these semi-arid regions today could help us predict effects in the rest of the Corn Belt in coming decades.

In this study, we examine maize yield impacts of low till practices in the western US Corn Belt (figure 1) using satellite-derived datasets at 30 m resolution. We apply published methods for mapping tillage practices (Azzari *et al* 2019) and crop yields (Deines *et al* 2021) to generate consistent data coverage in Kansas, Nebraska, South Dakota, and North Dakota from 2008 to 2020, and we designate irrigation status based on published annual irrigation maps (Xie and Lark 2021) to separately analyze rainfed and irrigated fields. We focus on long-term tillage practices by identifying fields with consistent high or low tillage for the entire 13 growing season study period. To assess causality based on observational satellite datasets, we implement the causal forests method, an adaptation of random forests algorithm designed to derive casual relationships from observational data (Athey and Wager 2019). We then use our results to identify specific counties that are currently under-adopting low till, despite potential yield increases.

2. Methods

2.1. Study area

Compared to the central Corn Belt, the western Corn Belt states of Kansas, Nebraska, South Dakota, and North Dakota that are the focus of this study (figure 1) experience less rainfall, shallower soils, and, consequently, more widespread irrigation, particularly in Nebraska (Green *et al* 2018). Rainfed crops routinely undergo periods of water stress (Grassini *et al* 2009). High till prevalence decreased from 28.1% to 18.8% between 2012 and 2017, corresponding with a 1.7% increase in no till and a 7.6% increase in other low till practices (USDA National Agricultural Statistics Service Cropland Data Layer 2022). Corn-soybean-corn is a major rotation in the region, comprising 15.4% of the cultivated area in South Dakota and 19.5% of the cultivated area in Nebraska, though there is also a large area that incorporates spring wheat rotations (Sahajpal *et al* 2014).

2.2. Datasets

2.2.1. Extending satellite-derived tillage classifications

We used previously published annual satellite-derived maps of tillage practices that categorize soybean fields as low till (encompassing both no till and strip till) or high till (encompassing all other practices expected to leave less than 30% of crop residue; Azzari *et al* 2019). The overall classification accuracy on validation points was 79%, with low till classified more accurately at 84%. Here, we extended the original dataset ending in 2016 through 2020 by applying the methods published in Azzari *et al* (2019) to generate a consistent map set of annual tillage practices spanning 2008–2020 for the study region. Generally, the satellite-derived tillage maps show that low till has increased during the study period, with differences visible by state (figure 2).

We then filtered the classified fields to only include those that had been constantly high or low till during the study period for three main reasons: (1) to isolate the effects of long-term tillage management of interest in this study, since research indicates that fields can experience an initial yield penalty following adoption of low till (Wade *et al* 2015, Pittelkow *et al* 2015a, Deines *et al* 2019a); (2) to increase our confidence in the tillage classification, since it is unlikely that the classifier would have incorrectly classified a field in all years; and (3) to increase our confidence that mapped tillage practices, which are based on annual soybean crop acreage, were also used in years when maize was grown. We therefore assumed that pixels with consistent classification in soybean years were under the same tillage management practice in maize years of crop rotations. This assumption is likely not universal, as tillage practices are crop specific for approximately 11% of farmers in this region (Wade *et al* 2015). We then generated 'field-like entities' (hereafter referred to as fields) from our pixel-level classification by isolating groups of connected pixels at least 40 pixels (3.6 ha) in size, avoiding small groups of pixels that may have been misclassified for various reasons (figure 3).

2.2.2. Expanding satellite-derived crop yield maps

To quantify field-level annual yields, we used a previously published yield mapping model based on the Scalable Crop Yield Mapper (SCYM; Lobell *et al* 2015). Briefly, this approach estimates crop yields from annual crop phenology obtained from satellite observations. Here, we used the SCYM model described in Deines *et al* (2021) to estimate 30 m pixel-level crop yields from Landsat satellite data. When evaluated on over 400 000 ground truth fields (yield monitor data) in the central Corn Belt (figure 1) between 2008–2018, the method was able capture 45% of maize yield variation at the field scale and 69% at the county scale (Deines *et al* 2021). Notably, SCYM was able to detect yield responses to soil and management factors not included in the model, and coefficients on these factors were similar to those that used ground-based yield measurements, increasing confidence in the model's accuracy and its suitability for agronomic analyses (Deines *et al* 2021). We extended the dataset to cover our full four-state study region through 2020. When we evaluated this extension on available ground truth fields in Nebraska, SCYM had an accuracy of $R^2 = 0.42$ for rainfed and $R^2 = 0.28$ for irrigated fields (see supplementary figures 1 and 2).

2.2.3. Satellite-derived irrigation data

We used the LANID irrigation maps (Xie and Lark 2021) to assign irrigation status for each field in our dataset. Briefly, LANID maps irrigation at Landsat's 30 m pixel resolution for the full contiguous United States annually from 1997–2017. The mapping algorithm performs well, with Nebraska and Kansas having Kappa values of 0.91, indicating good agreement between the model and ground truth. We classified fields irrigated greater than 3 times between 2008 and 2017 as irrigated; remaining fields were classified as rainfed, allowing for some misclassification of irrigation status that can occur in years with abundant rainfall and the inclusion of fields that may have had irrigation installed from 2018–2020 (Pervez and Brown 2010, Deines *et al* 2019b). We note that because LANID data ends in 2017, some of the fields that we classified as rainfed may have met our criteria for 'irrigated' with data from additional years or with the addition of new irrigation systems. Given our findings (section 3), the possible inclusion of some irrigated fields as rainfed likely indicates that

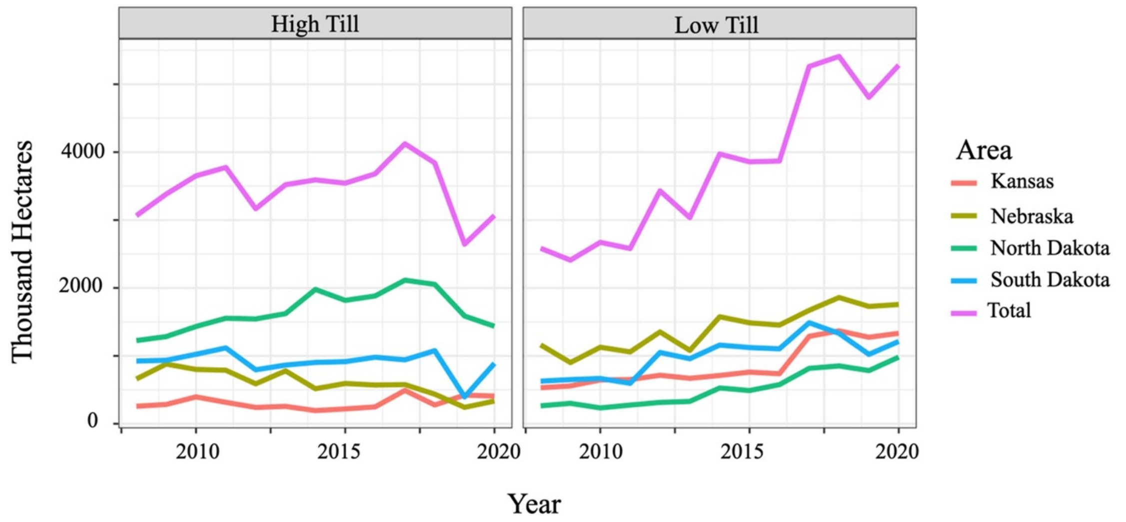

Figure 2. Tillage trends in study region from satellite-based maps of tillage practices based on soybean acreage (Azzari *et al* 2019). High till is defined as having < 30% of crop residue left on fields and corresponds to conventional high-intensity tillage practices, while low till is defined as leaving > 30% of crop residue and includes both strip till and no till.

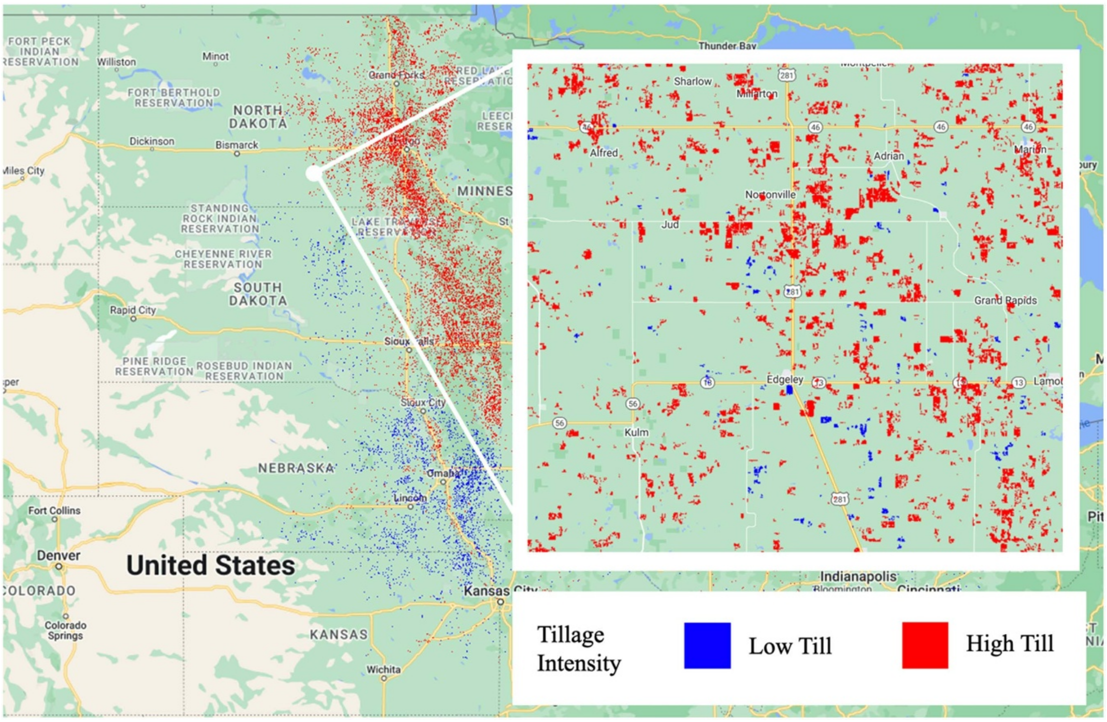

Figure 3. Long term low till and high till fields based on satellite-derived tillage maps for 2008–2020.

our estimated yield impacts are conservative for rainfed fields.

2.3. Environmental covariables

For each field in our dataset, we had extracted 48 climate and soil variables using existing gridded datasets. We retrieved 30 year climate normals (1981–2010) from the PRISM dataset at 4 km resolution (Daly *et al* 2008, 2015) to characterize long-term climate, as well as monthly weather data from GRIDMET and TerraClimate at 4 km resolution (Abatzoglou 2013, Abatzoglou *et al* 2018) to relate to annual yield outcomes. We extracted soil data for the top 1 m of soil from the Polaris dataset (Chaney *et al* 2016) to quantify clay, silt, and sand proportions, mean bulk density, and pH. The USDA gSSURGO database provided two derived soil variables, root zone available water storage and soil organic carbon, at 30 m resolution (Soil Survey Staff 2020). Additionally, we created the variable 'previous decade corn:soy' (simply the ratio of growing seasons of corn to soy grown in the previous decade) using the

Table 1. Variables used in causal forest analysis of rainfed fields, ordered by variable importance with highest importance listed at the top of each column. VPD = vapor pressure deficit; SOC = soil organic carbon.

Treatment propensity (30 year climate normals)	Expected yield outcome	Treatment effect
July VPD	Year	May minimum temperature
Slope	Previous decade corn:soy	April maximum temperature
April precipitation	July VPD	August minimum temperature
May precipitation	August VPD	Slope
pH	August minimum temperature	June–August solar radiation
June VPD	Root zone available water storage	Sand
Root zone avail water storage	June–August solar radiation	Early season precipitation
Soil organic carbon	April maximum temperature	Bulk density
April temperature	May minimum temperature	SOC
Clay	June climatic water deficit	Root zone available water storage
Bulk density	June precipitation	April soil moisture
May temperature	July climatic water deficit	May precipitation
June precipitation	Growing season precipitation	Previous decade corn:soy
July temperature	Bulk density	Growing season precipitation
July precipitation	May precipitation	August VPD
August temperature	May soil moisture	August climatic water deficit
June temperature	Soil organic carbon	July precipitation
Sand	August climatic water deficit	May soil moisture
Silt	Early season precipitation	June precipitation
	April soil moisture	July VPD
	Sand	June climatic water deficit
	July precipitation	July climatic water deficit
	Slope	Year

Table 2. Variables used in causal forest analysis of irrigated fields, ordered by variable importance with highest importance listed at the top of each column. VPD = vapor pressure deficit; SOC = soil organic carbon.

Treatment propensity (30 year climate normals)	Expected yield outcome	Treatment effect
Slope	Year	pH
SOC	Growing degree days	Clay
June precipitation	August climatic water deficit	Sand
July precipitation	August maximum temperature	Root zone available water storage
Silt	August precipitation	Slope
June VPD	pH	Previous decade corn:soy
April Temp	May minimum temperature	April soil moisture
July VPD	Growing season precipitation	August precipitation
May precipitation	June precipitation	May precipitation
April precipitation	Previous decade corn:soy	SOC
Sand	July VPD	July minimum root zone moisture
Bulk density	Root zone available water storage	Growing season precipitation
Root zone available water storage	July maximum temperature	Aridity
July temperature	April soil moisture	Year
May temperature	Aridity	August maximum temperature
June temperature	Sand	July maximum temperature
August temperature	June–August solar radiation	Growing degree days
Clay	May precipitation	May minimum temperature
pH	April precipitation	June–August solar radiation
	July root zone moisture	July VPD
	June climatic water deficit	June precipitation
	Slope	June climatic water deficit
	SOC	

USDA Cropland Data Layer (CDL; Boryan *et al* 2011) to quantify crop rotation dynamics. Tables 1 and 2 provide a full list of variables used for each analysis, which have been subset separately for each analysis (details in supplementary text 1).

2.4. Causal forest analysis

Because we use observational satellite data, identifying causal effects of low till practices on maize yields could be confounded if there were correlations among tillage practices and other factors that also affect yields. To account for this, we used causal forests, a machine learning approach that adapts the random forests algorithm (Breiman 2001) to estimate treatment effects using observational data (Athey *et al* 2019). Outcomes for each treatment observation are compared against all available control observations, weighted by similarity. When estimating treatment effects, causal forests guard against confoundedness by using a 'doubly robust' method termed augmented inverse-propensity-weighted estimation (Robins and Rotnitzky 1995). This method weights treatment effects using treatment propensity weighting–in our case, how likely a field is to receive low till–and includes a regression adjustment based on a model specifying the expected outcome–in our case, a yield model. Other advantages of the causal forests approach include the ability to generate mathematically valid confidence intervals, a robustness to nonlinear interactions and large numbers of covariates, and the ability to detect and quantify heterogenous treatment effects (Wager and Athey 2018, Athey *et al* 2019, Farbmacher *et al* 2019, Baiardi and Naghi 2020, Strittmatter 2021).

Here, we implemented separate causal forests analyses for rainfed and irrigated fields using the 'grf' package in *R* (Tibshirani *et al* 2018). In this application, we considered low till as the treatment, high till as the control, and maize yield as the outcome. To model the likelihood of treatment for each field, we used only static variables providing long-term characteristics of each field relevant to tillage adoption (soil properties, field slope, and climate normals). To meet the assumption of overlap (suppplementary text 1), we excluded fields with very high (>0.95) or very low (<0.05) likelihoods of treatment (Athey *et al* 2019). This filtering resulted in the final sample sizes of 47 942 rainfed fields (24 635 high till and 23 307 low till) and 35 514 irrigated fields (18 739 high till and 16 775 low till). Variables used in each sub-model are provided in table 1 (rainfed) and 2 (irrigated), sorted by variable importance based on the number of times each variable was used as a split in an individual tree. All other details on the implementation of the causal forests analysis can be found in supplementary text 1.

Results are reported as the average treatment effect (ATE) with a 95% confidence interval, representing an average of the field-level treatment effects. On the subgroups of fields that received treatment and fields that did not receive treatment, we computed two other population-level metrics: the average treatment effect on the treated (ATET) and average treatment effect on the control (ATEC). The ATET represents the effect of low till on fields that received low till, while the ATEC represents the effect of expanding low till to fields that received high till. A positive ATET indicates that the fields that receive low till are benefitting from the practice, while a positive ATEC indicates that the high till fields would benefit from expanding low till.

Treatment effects can often vary non-randomly by subpopulation, a case known as heterogeneity of treatment effect. To identify factors affecting the strength and direction of yield impacts from low till, we first tested for significant heterogeneity using the 'test_calibration' function in grf. Finding significant levels, we then grouped observations by the magnitude and direction of their predicted conditional average treatment effect (CATE; negative, small positive, and large positive yield effects) and examined covariate values among these groups. We also mapped treatment effects in space by averaging the CATE's of all observations on a 5 km^2 grid across the study area.

2.5. Identification of high priority counties

The treatment effect on the control group (ATEC) provides insight into the effect of performing low till on fields that received high till. A positive treatment effect in the control group indicates that the fields that received high till would have higher yields under low till. We used this metric to identify counties that may be high priority for expanding low till methods. First, we used our model to estimate the yield difference between tillage types for each county by multiplying the treatment effect of each rainfed, high till (control) field by the field's size in hectares. We then summed this yield difference to the county level and identified counties with net positive treatment effects and a rate of low till that is below that of the regional mean, which was 81% based on the 2017 NASS Census.

3. Results

3.1. Conservation tillage increases yields in rainfed fields

We found that low till significantly increased yields in rainfed fields. The average (field-level) treatment effect of low till on rainfed fields in the western Corn Belt was 0.99 t ha^{-1} (95% CI: [0.967, 1.012]). With a mean yield of roughly 10 t ha^{-1} in the region, the treatment effect translates to a 9.9% yield increase (95% CI: [9.68, 10.14]). Conditional treatment effects were strongest in the northern part of our study area, and the relatively few locations (6.3% of observations) with yield penalties were clustered in the southern portion (figure 4). In contrast to rainfed fields, the ATE of low till on irrigated fields was not significant (−0.008 t ha^{-1}; 95% CI: [−0.036, 0.019]).

3.2. Identifying relationships between field characteristics and yield impact

For rainfed fields, several covariates were strongly associated with heterogeneity of yield effects (figure 5). Fields with the most positive treatment effects had lower April maximum temperature, August minimum temperature, June–August solar radiation, May minimum temperature, early season precipitation and higher sand and soil organic carbon. We do not report heterogeneity of

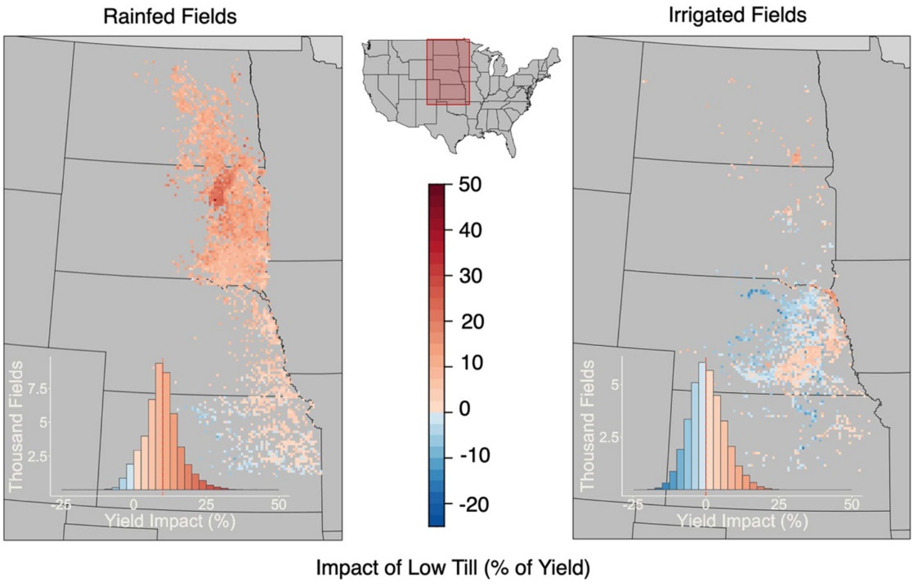

Figure 4. Spatial distribution of maize yield impacts from low till on rainfed (left) and irrigated (right) fields based on the mean conditional treatment effect for all observations within a regular 5 x 5 km grid mesh. Histogram legend provides the distibution of treatment effects across all observations. The average treatment effect is indicated with the dotted red line.

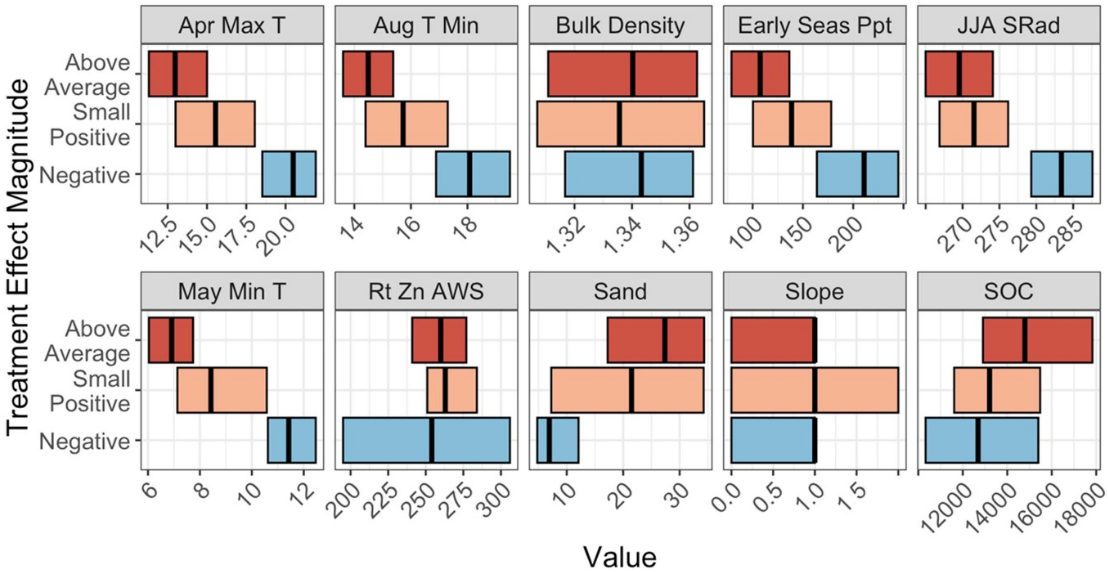

Figure 5. The 10 most important environmental covariates associated with yield impacts from conservation tillage for rainfed fields (see table 1), ordered alphabetically. The interquartile range is displayed, and observations are grouped by their estimated treatment effect from the causal forests analysis. T = Temperature, Seas = Season, SRad = Solar Radiation, M = Moisture, Ppt = Precipitation, Rt Zn AWS = Root Zone Available Water Storage, SOC = Soil Organic Carbon; JJA = June, July, and August.

effects for irrigated fields, since overall effects were insignificant.

3.3. The effect of low till in treated and untreated fields

Based on the ATEC, implementing low till on rainfed fields would lead to an average 9.58% yield increase (95% CI: [9.08, 10.07]). In irrigated fields, performing long term low till on the fields that received long term high till has a non-statistically significant treatment effect (95% CI: [−0.476, 0.579]) (figure 6).

We found that 108 of the 134 counties in our analysis could see improved yields if fields that received long term high till had received long term low till (red counties, figure 7(b)). These counties were primarily in the northern part of the study area. Combined with data on the rate of low till in each county based on the 2017 USDA NASS Census (figure 7(a)), we were able to identify 41 high priority counties that could benefit from low till but have below average rates (figure 7(c)). The high priority counties are clustered in the northern and eastern parts of the study area.

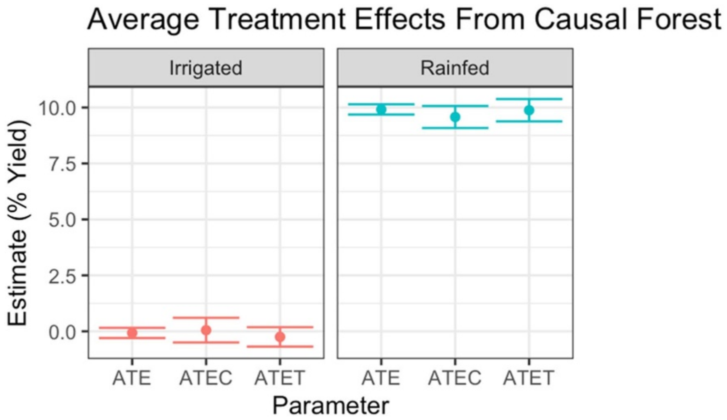

Figure 6. 95% Confidence intervals for the average treatment effect (ATE), average treatment effect on the control (ATEC), and average treatment effect on the treated (ATET) for irrigated and rainfed fields.

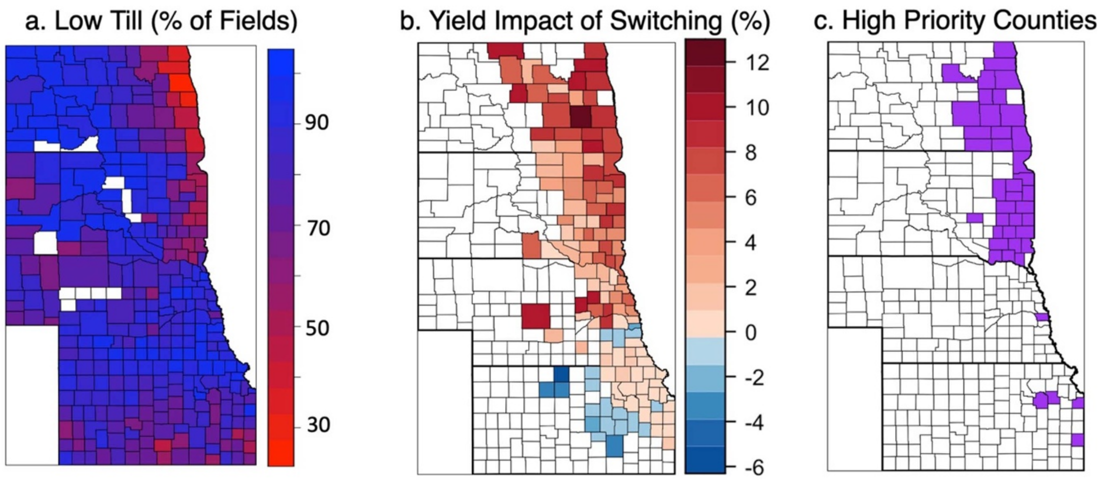

Figure 7. Identification of counties likely to benefit from increased use of low till methods. (a) The percent of agricultural area under low till in 2017 based on USDA data. (b) The estimated yield impact of switching the long term high till rainfed fields to long term low till in each county. (c) Counties identified as high priority for switching based on having a percentage of low till rainfed fields less than the regional average (<81%) and positive net yield impact from switching long term high till rainfed fields to long term low till.

4. Discussion

4.1. The effect of low till on yield

This study found that long-term low till from 2008 to 2020 resulted in a 9.9% yield increase in the rainfed fields of the western US Corn Belt. The highest yield benefits occurred in conditions related to water stress, including low early season precipitation and sandy soils (figure 5). A study on primarily rainfed fields in the central Corn Belt (figure 1) found that low till causes a 3.3% yield increase in maize on average across the region, with some of the highest positive impacts in South Dakota, the only state which overlaps with this study's area of interest (Deines *et al* 2019a). Similarly, the global meta-analysis performed by Pittelkow *et al* (2015b) found low till to perform best in dry, rainfed systems for several crops including maize. Together, these studies provide evidence that long term low till leads to higher yield benefits in more arid climatic conditions, since the soil moisture benefits of low till will be especially important in systems with higher water stress.

We found that fields that experienced the largest yield benefits from low till had the highest levels of soil organic carbon and the fields that experienced yield decreases had low levels of soil organic carbon (figure 5). Due to the impact of organic matter on aggregate stability and thus water availability, it has previously been suggested that highly degraded fields will not accumulate sufficient organic matter to realize soil structure changes (Page *et al* 2013, Lal 2020) and thus yield impacts, which our results support.

The importance of improved water availability via low till is further highlighted by the absence of yield benefits for irrigated fields (figure 6). The presence of irrigation has been found to reduce the impact of soil characteristics on soybean yields (Elgi and Hatfield 2014). A study of irrigated corn in the southwestern

US also found no effect of tillage practice on yield (Idowu *et al* 2019). Under irrigation, the water savings benefits of low till would be less relevant, as irrigation is supplied to meet crop requirements, making yields similar between high and low till. Our results do demonstrate, however, that farmers on irrigated fields can generally adopt low till without a yield penalty, and potentially experience the lower operating costs associated with low till (Weersink *et al* 1992).

Our results suggest that low till can be a successful strategy even in areas with colder temperatures often thought to benefit from tillage used to warm the soil. We identified rainfed fields with low April maximum temperature, low May minimum temperatures and low August minimum temperature as benefitting most from conservation tillage. Though this may seem to complicate water stress as the primary driver of yield impacts, the moderate negative correlation between the temperature variables and soil sand content prevents too strong of an interpretation of these results (see supplementary figure 3). These variables may be important because of their correlation with sand content, or they may be important in their own right. Low temperatures may help reduce weed pressure (Peters *et al* 2014), as well as other common issues such as pests, plant diseases, and herbicide-resistant weeds can be a bigger problem under low till (Page *et al* 2013, Cordeau *et al* 2020). Although our observational analysis is unable to identify the mechanism, it identifies areas for future research with randomized controlled field studies. It is unclear whether fields see the greatest treatment effects despite or because of lower temperatures, but our results demonstrate that low till can be beneficial even on fields with low spring temperatures.

4.2. Implications for expanding conservation tillage

Although low till is increasing on the landscape, there remain areas with low rates of adoption relative to the regional average (figure 7(a)). We identified specific counties that would likely experience a yield increase from further adopting low till practices (figure 7(c)). Based on our calculations, switching to low till on rainfed fields included in the analysis could increase total agricultural production by 12 226 tons when accounting for field size, or 4.29% of the current production on those fields.

Meaningful collaborations between farmers and researchers and the dissemination of ideas through agricultural extension and workshops have played a vital role in the history of low till adoption (Islam and Reeder 2014). Our identification of high priority counties aims to supplement these partnerships, providing a spatially-explicit, data-driven approach that allows efforts to be focused in specific counties as well as increasing confidence by accounting for site-to-site variation.

4.3. Further considerations

There are several variables which could be relevant but were not available on the spatial scale of this study, such as herbicide inputs and fertilizer inputs, among others. Wade *et al* (2015) note that the benefits of low till are amplified when used with cover crops, and that the likelihood of adopting low till is somewhat correlated with factors such as education level and owning versus leasing land, none of which were available on the scale of this analysis. However, the doubly-robust propensity score approach combined with the matching of fields similar in their covariate distributions in the causal forest analysis mitigate the impact of confounding variables (Athey *et al* 2019). In the absence of spatially explicit datasets of confounding variables, field studies remain the best way to understand how these may impact yield responses.

Like all management decisions, the decision to adopt a low till system involves weighing a variety of tradeoffs. Though low till has long been associated with decreased labor and machinery costs, herbicide costs for weed control and disease risk can be higher under low till and may offset savings on some fields (Weersink *et al* 1992, Williams *et al* 2000). Tillage decisions are a part of a suite of related decisions, including conservation crop rotations, multi-cropping, cover-cropping, fallowing, and the use of herbicide resistant seeds (Classen *et al* 2018). The information provided by this study will be of use to decision makers who can consider a fuller list of criteria.

5. Conclusions

This study provides evidence that the adoption of low till leads to higher yields for rainfed fields (by an average of 9.9%) in the semi-arid western Corn Belt region of the US. Understanding the impacts of low till on fields in the western Corn Belt is of interest to the entire central Corn Belt, where climate change is expected to lead to increased summer water stress, making it more like today's western Corn Belt (Bhattarai *et al* 2017, Ting *et al* 2021). Moreover, yield impacts are not the only potential benefit of low till, which is associated with lower labor, fuel, and machinery costs than conventional high till approaches (Weersink *et al* 1992). Beyond direct agronomic and economic benefits, low till can also have positive environmental effects, such as by reducing soil erosion, carbon emissions, and local air pollution (Behrer and Lobell 2022). Our results suggest that these benefits can be realized without a negative impact to crop yields in most cases.

Data availability statement

The data that support the findings of this study are openly available at the following URL/DOI: https://doi.org/10.5281/zenodo.10622375.

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