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LETTER

Satellites reveal a small positive yield effect from conservation tillage across the US Corn Belt

Jillian M Deines[1], **Sherrie Wang**[1,2] and **David B Lobell**[1]

[1] Department of Earth System Science, Center on Food Security and the Environment, Stanford University, United States of America

[2] Institute for Computational and Mathematical Engineering, Stanford University, United States of America

E-mail: jillian.deines@gmail.com

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Abstract

Conservation tillage is a primary tenet of conservation agriculture aimed at restoring and maintaining soil health for long-term crop productivity. Because soil degradation typically operates on century timescales, farmer adoption is influenced by near-term yield impacts and profitability. Although numerous localized field trials have examined the yield impacts of conservation tillage, their results are mixed and often unrepresentative of real-world conditions. Here, we applied a machine-learning causal inference approach to satellite-derived datasets of tillage practices and crop yields spanning the US Corn Belt from 2005 to 2017 to assess on-the-ground yield impacts at field-level resolution across thousands of fields. We found an average 3.3% and 0.74% yield increase for maize and soybeans, respectively, for fields with long-term conservation tillage. This effect was diminished in fields that only recently converted to conservation tillage. We also found significant variability in these effects, and we identified soil and weather characteristics that mediate the direction and magnitude of yield responses. This work supports soil conservation practices by demonstrating they can be used with minimal and typically positive yield impacts.

1. Introduction

Tillage has been a component of global agricultural systems for millennia. Turning over the soil helps control weeds, break up compaction, and mix nutrients [1]. This repeated disturbance, however, produces unnaturally high erosion rates in agricultural fields [2], harms soil biota [3], and damages soil structure [4]. Combined with other soil pressures, this has resulted in widespread degradation [5] and cropland abandonment at rates exceeding 10 million hectares per year over the past century [6–8]. These losses pose a serious challenge to meeting current and future global food demand.

To combat these negative effects, conservation tillage is promoted to restore and maintain soil health for long-term crop productivity. It is characterized by the retention of at least 30% of crop residues on the soil surface and often achieved through low-impact tillage techniques such as no-till or strip till [9]. These residues and reduced soil disturbance help prevent erosion [2], improve water retention and drainage [10, 11], and foster the quantity and quality of organic matter [4, 12, 13]. After emerging in response to the 1930s Dust Bowl in the United States (US), large-scale adoption began in the 1980s and 1990s following the development of modern herbicides and specialized technology [1, 14, 15]. Today, conservation tillage is practiced on over 150 million ha worldwide, with adoption concentrated in South America, Oceania, and North America [14–16].

Because soil degradation typically operates on century timescales, near-term yield impacts and profitability are key factors for farmer adoption [17, 18]. Numerous studies have examined the yield effects of conservation tillage, and their results are mixed. A recent global meta-analysis concluded that no-till reduced yields by 5.1% in aggregate, although substantial variability existed among crops and biomes [16]. While maize yields remained lower regardless of

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duration, all other crop categories did achieve similar (but not higher) yields to conventional tillage after 5+ years, suggesting an initial yield penalty due to an adjustment period [16]. In contrast, other studies have found no or even positive yield impacts for maize [19–23] along with variable effects by soils, weather, and/or rotation practices [16, 19, 22–24]. Soybean yields are typically found to be indistinguishable among tillage practices [16, 19–21, 25], with some exceptions [26–28].

Ultimately, a paucity of real-world conditions across biophysical gradients in the literature limits insights meaningful for practitioners. Many studies involved small-scale research plots on level ground with good soils, prohibiting the use of field-scale equipment, inclusion of sloped fields, and a range of soil quality, all cases that may favor conservation tillage [16, 29]. Although research plots enable randomized trials to isolate tillage effects, identical regimes for other management factors are not representative of on-farm operations adapted to tillage type [13, 30, 31]. A rare comparison of production-scale systems found no yield differences for both maize and soybeans in the upper midwestern US, but it was limited to two locations [29]. Combined with anecdotes of adoption rates exceeding expectations from economic studies [32], there are indications that production scale effects may differ from research plot studies.

Crop information derived from satellite imagery provides a complementary approach to randomized trials that can capture on-farm characteristics at subfield-level resolution across regional scales at low costs. With recent improvements in cloud-computing resources and imagery access, maps of crop-specific yields and tillage practices can be generated annually over decades, particularly in large commercial systems [33–35]. These advances allow a dramatic increase in sample size and regional coverage that ensures a wide representation of biophysical conditions, weather, and on-farm management practices. In addition, ongoing innovations in causal inference methodologies increasingly enable the identification of causal relationships from observational data, including methods to account for sampling biases and confoundedness.

Here, we use recently published satellite estimates of tillage practices [35] and crop yields [34, 36] extracted from 30 m Landsat imagery to examine the yield effects of conservation tillage for both maize and soybeans in the US Corn Belt from 2005 to 2017. We leverage causal forests, an emerging forest-based machine learning approach designed to estimate treatment effects in observational data [37–39], to quantify yield impacts of conservation tillage across soil and weather conditions. Because we lack data on management practices accompanying tillage type, we ask the question, 'What are the yield impacts of the full management regime for conservation tillage compared to the regime in conventionally tilled fields?' In this way, we address the knowledge gap concerning on-farm yield impacts from conservation tillage systems to further inform evidence-based management by practitioners.

2. Methods

2.1. Study area

The US Corn Belt encompasses approximately 1 million km^2 across 12 states in the midwestern United States [40]. It is characterized by high-yielding commercial agriculture predominantly in maize-soy rotation, contributing over one third of global production for these crops [41]. Here, we focused on a 9-state region for maize (figure 1(a)) and 3 states (Indiana, Illinois, and Iowa) for soybeans due to yield map availability for each crop (section 2.2). This region has primarily hot-summer to warm-summer humid continental climates (Koeppengeiger classes Dfa and Dfb) [42], and most fields do not receive supplemental irrigation. According to the US Agricultural Census [43], conservation tillage covered 50% (~412 000 km^2) of total cropland area in the 9-state region in 2017, a 17% increase since the previous 2012 Census. Cover cropping, a complementary practice promoted along with reduced tillage and crop rotation as the three pillars of 'conservation agriculture,' is not nearly as prevalent, covering only 3.4% of total cropland area in the 2017 Census. Still, this represents a 75% increase since 2012 [43]. Increasing adoption of these soil conservation practices has reduced average erosion rates in the United States ~35% between 1982 and 2007, but rates remain above natural soil production [44].

2.2. Satellite-derived data sources

We used a previously published gridded dataset of annual tillage practices for the north central US from 2005 to 2016 by Azzari *et al* [35] to identify locations practicing conservation or conventional tillage at 30 m resolution (figure 1(a)). Briefly, these maps were generated by applying a random forest classifier trained on ground truth data from 5866 soybean fields to Landsat satellite imagery. Because the ground truth data was limited to soybean fields, the classification was applied only to pixels identified as soybeans based on annual crop type maps from the US National Agricultural Statistics Service (NASS) [45]. These soybean-based tillage maps achieve fairly complete coverage of the study region every two years due to dominant maize-soybean rotations. Here, we assume that the same tillage method was practiced during subsequent maize years. It is likely this assumption is not universally valid, since partial adoption characterizes over half of conservation tillage practitioners, with approximately 11% of farmers in this region adopting tillage practices by crop type [46]. Similarly challenging for inference, this product has an overall accuracy of 79%, with 84% and 72% of validation points correctly classified for conservation and

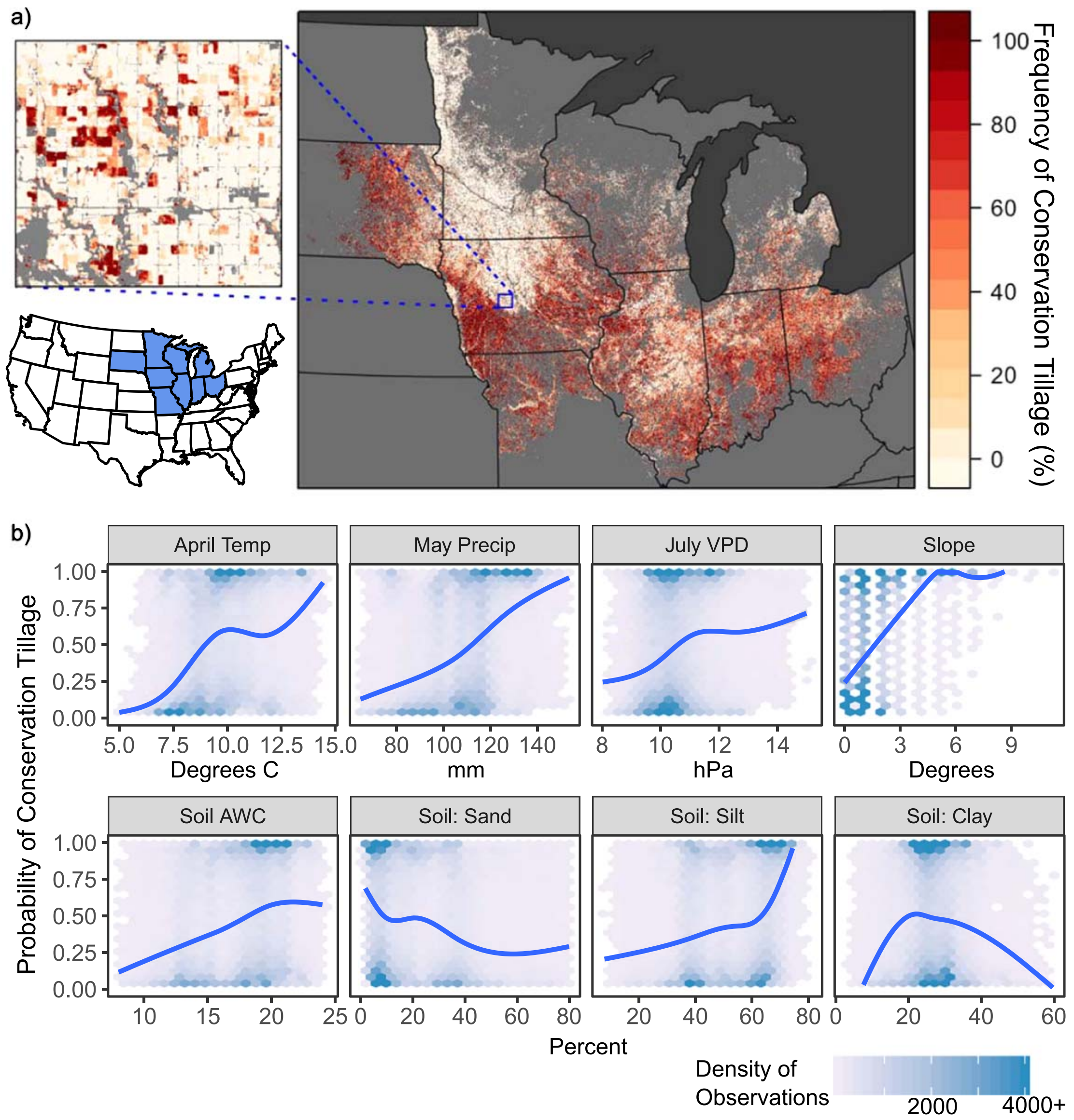

Figure 1. Satellite-derived tillage practices in the study area and environmental factors associated with long-term conservation tillage. (a) Study area inset and map of tillage frequency between 2005 and 2016. Tillage frequency was derived from 30 m Landsat data and is reproduced from Azzari *et al* 2019 [35]. Zoomed inset demonstrates variability on the landscape even in areas with a dominate tillage type. (b) Conditional probabilities of conservation tillage by environmental covariables from treatment propensity model. Estimates from individual field observations were smoothed with a GAM (blue line), and the density of field observations is indicated with blue shading. AWC = available water content; VPD = vapor pressure deficit.

conventional tillage, respectively. We mitigate these potential sources of error through additional data filtering criteria (section 2.3) and note that, given our findings (section 3.2), the possible inclusion of a small percentage of misclassified maize fields implies that our estimates of yield differences between conservation and conventional tillage systems are likely conservative.

Previously published yield maps for maize and soybean were produced using the Scalable Crop Yield Mapper (SCYM) [33], a satellite-based approach with a demonstrated ability to detect impacts from management practices [47, 48]. This approach has two main steps. First, statistical models predicting yields from crop phenology and climate covariates are derived from regionally parameterized crop models. Second, these statistical models are applied to satellite imagery and gridded climate datasets based on crop type maps, generating a yield estimate for each pixel. Maize yield maps were produced with Landsat satellite imagery for nine Corn Belt states from 2008 to 2015 by Jin *et al* [34]. We used the algorithm described therein to extend maize yield maps through 2017, with overall county-level agreement at $r^2 = 0.78$ (RMSE = 1.2 t/ha) compared with NASS statistics. Soybean yield maps were produced by Lobell and Azzari [36] for the states of Indiana, Illinois, and Iowa from 2000 to 2015 with similar agreement to county yield statistics ($r^2 = 0.74$, RMSE = 0.16 t/ha). Figure S1 (figure S1 is available online at stacks.iop.org/ERL/14/124038/mmedia) shows mean yields across space for each crop during the study period.

2.3. Field sample generation and covariate sampling

As noted above, the tillage map classification performs moderately well but contains some errors that could add noise to our analyses. To guard against spurious classifications, we restricted the tillage maps in the following ways: (1) we required pixels to have 6 observations during the 12 year dataset, with at least one observation before 2008 and after 2014, to ensure a dense time series of observations spanning the data record; (2) from these, we identified long-term tillage management regimes based on pixels with constant tillage status in all observations, indicating at least a decade of conservation practices and likely increasing the probability of sustained adoption in maize years; (3) we identified 'single-switch' pixels which switched tillage status one time between 2009 and 2014 to examine the impact of new tillage regimes; and (4) pixels needed to be part of a coherent pixel group of the same tillage classification and, for single-switch pixels, the same year (see Text S1). All remaining sampling and analyses occurred at this 'field entity' level. We then used a data-driven delineation of climate-soil domains [26] to sample up to 500 fields per tillage status within each domain for each year, resulting in 144 127 and 117 757 maize field-years and 92 037 and 100 222 soybean fields-years for conventional and conservation tillage, respectively.

For each field, we extracted the median yield from SCYM maps. We removed fields with outlier yield values below the 0.01% and above the 99.99% from both maize and soybean datasets. We then extracted median field values for a suite of environmental covariables defining both static field properties and annually varying weather and soil moisture. For static field properties, we obtained 1981–2010 climate normals from PRISM [49, 50], calculated field slope from the USGS National Elevation Dataset [51], and extracted soil properties for the top one meter from the SSURGO soil database [52]. Annual monthly and seasonal weather summaries were extracted from GRIDMET ~4 km meteorological dataset [53]. Annual monthly modeled soil moisture and climate water deficit were extracted from the TerraClimate ~4 km climatic water balance dataset [54]. Table S1 provides a list of all variables considered and their data sources. All data were accessed and processed in Google Earth Engine [55] with the exception of the soil data, which we acquired through SSURGO.

2.4. Analysis with machine-learning based causal inference

To quantify conservation tillage's impact on crop yields, we used causal forests, an recent adaptation of the classic random forest algorithm [56] for statistical inference on causal effects, particularly when heterogeneity is present [38, 39]. Broadly, causal forests act as an adaptive kernel method [39]; in our application, it uses each field's closest neighbors in covariate space to generate a counterfactual yield estimate under the alternative tillage practice. Causal forests generate mathematically valid confidence intervals while leveraging the ability of random forests to handle many covariates and nonlinear interactions without overfitting or requiring explicit model specification [38, 39, 57, 58]. Recent applications demonstrate better performance than conventional econometric methods for detecting and quantifying heterogenous treatment effects [59, 60].

Causal forests are also designed for observational datasets. Because treatments are not randomly assigned, an observational analysis could be confounded if fields that have higher (or lower) yields also tend to adopt conservation tillage at higher rates. Causal forests addresses these biases with a 'doubly robust' treatment estimation method (augmented inverse-propensity weighted estimation [61]) which combines both treatment propensity weighting [62] and regression adjustment to reduce sensitivity to misspecification in either model [39, 63].

2.4.1. Analysis of long-term conservation tillage

Here, we used the 'grf' package [64] in R [65] to implement causal forests separately for maize and soybean fields with long-term tillage practices (section 2.3). We designated 'conservation tillage' as the treatment variable, 'conventional tillage' as the control, and crop yield as the outcome. First, we used the full set of static covariates describing field slope, soil properties, and climate normals (tables 1 and 2) to estimate treatment propensity using 2000 trees and default function settings. The propensity model performed well, indicated by close agreement between propensity scores versus treatment status (figure S3). To examine biophysical factors typically associated with conservation tillage, we used the larger 9-state maize domain. We inferred variable importance from the number of times each covariate was used to split the individual trees, although it should be noted that correlations among variables can skew these metrics [66].

To meet the assumption of overlap within the causal forests framework, which requires that treatment and control samples occupy similar covariate space to provide appropriate neighbors for comparison, we then removed samples with propensity scores below 0.05 or above 0.95. This produced a final dataset of 70 404 and 88 220 (maize) and 51 215 and 68 334 (soybeans) unique field-year observations for conservation and conventional tillage, respectively. Figures S4 and S5 provide the spatial distribution of field observations before and after this propensity filter. We then specified the regression adjustment portion of the doubly robust estimator (see Text S2 and figure S2). Next, we used all covariables selected for this regression model and the most important variables in the propensity model (tables 1 and 2) to estimate the treatment effects of conservation tillage using the 'causal_forest' function in grf with 2000 trees and default parameters.

Table 1. Variables used in causal forests analysis: Maize. Variables are ordered by the proportion of splits on each variable within the ensemble of decision trees that make up each forest (high to low), which provides a rough approximation of variable importance. VPD = vapor pressure deficit; AWC = available water content. Table S1 provides data source information.

Treatment propensity (30 yr climate normals)	Regression adustment/Expected yield outcome	Treatment effect
Slope	July mean max temp	Slope
May precip	May mean max temp	Soil clay content
April mean temp	Year	Soil sand content
April precip	July climate water deficit	June precip
July VPD	Solar radiation (June–August)	April soil moisture
June precip	August mean max temp	May mean min temp
July precip	May mean min temp	Early season precip
June VPD	June precip	August soil moisture
Soil sand content	Early season precip	Soil AWC
June mean temp	August soil moisture	June mean min temp
Soil silt content	June mean min temp	May mean max temp
Soil AWC	Growing Degree Days	June climate water deficit
May mean temp	May precip	July VPD
August mean temp	July precip	July mean max temp
July mean temp	August mean min temp	May precip
Soil clay content	Soil clay content	Growing Degree Days
Soil ksat	Soil AWC	April precip
	Soil sand content	Solar radiation (June–August)
		August mean min temp
		August mean max temp
		July precip
		April mean temperature
		July climate water deficit
		Year

Table 2. Variables used in causal forests analysis: Soybeans. Variables are ordered by the proportion of splits on each variable within the ensemble of decision trees that make up each forest (high to low), which provides a rough approximation of variable importance. VPD = vapor pressure deficit; AWC = available water content. Table S1 provides data source information.

Treatment propensity (30 yr climate normals)	Regression adjustment/Expected yield outcome	Treatment effect
Slope	Aridity (June–August)	May soil moisture
May precip	Previously Soy	April soil moisture
April mean temp	July climate water deficit	Slope
Soil silt content	Solar radiation (June–August)	July soil moisture
June VPD	June precip	Soil silt content
April precip	Growing Degree Days	July precip
Soil clay content	May soil moistre	Aridity (June–August)
July precip	June climate water deficit	Soil clay content
June precip	May precip	Soil sand content
May mean temp	Jan–April precipitation	June precip
August mean temp	July precip	August mean min temp
July mean temp	July soil moisture	Growing Degree Days
Soil AWC	Soil sand content	Soil AWC
June mean temp	April precip	July VPD
July VPD	June–August precip	Early season precip
Soil sand content	Soil clay content	Solar radiation (June–August)
Soil ksat	August mean min temp	April mean temp
	Year	May precip
		Growing season precip
		Previously Soy
		April precip
		June mean min temp
		Year
		June climate water deficit
		July climate water deficit

To investigate heterogeneity in treatment effects, we first tested for significant heterogeneity using the 'test_calibration' function in grf. We then summarized covariate values for subpopulations of observations based on their predicted treatment effects. Figures 2(a) and 3(a) show the distribution of

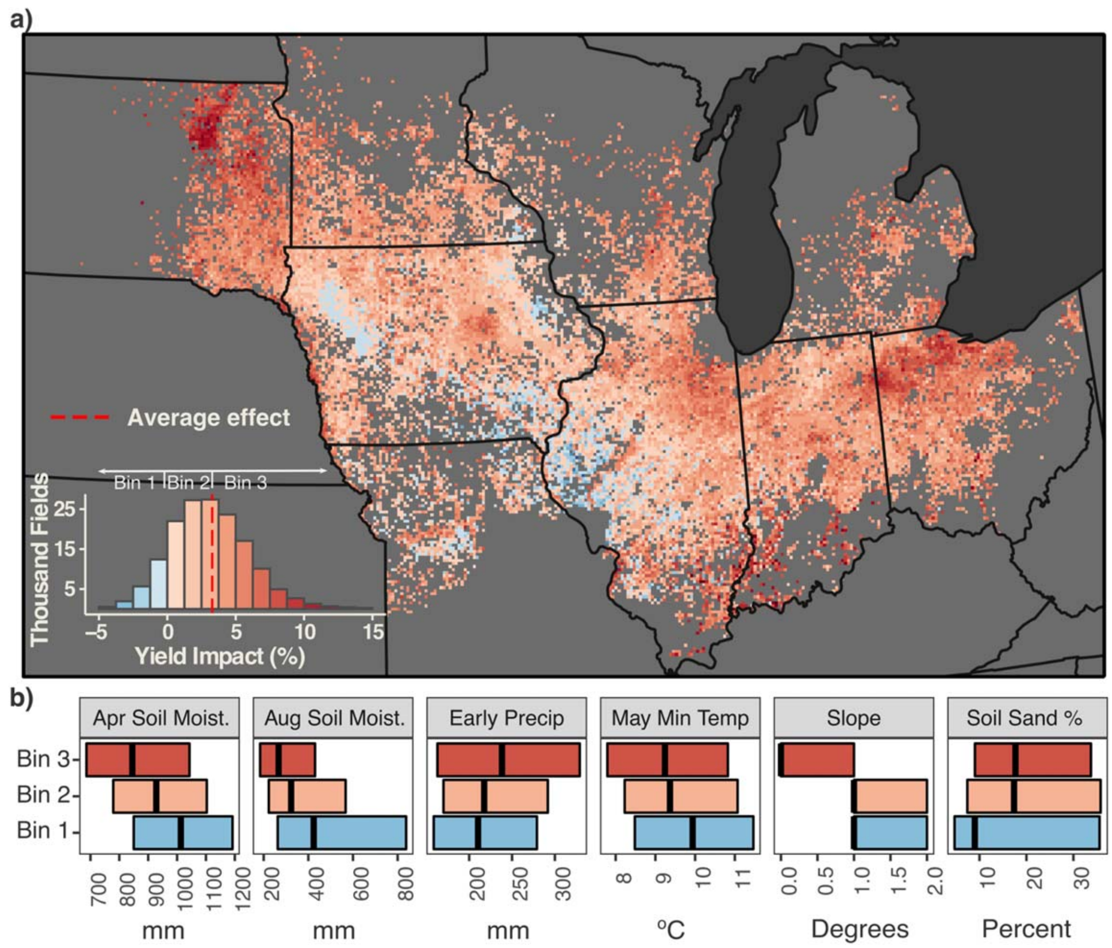

Figure 2. Distribution of maize yield impacts from conservation tillage from 2008 to 2017. (a) Mean conditional treatment effect for all field-year observations on a regular 5 km^2 grid. The distribution of treatment effects across all 158, 624 field observations is provided in the histogram, with indicators for subpopulation bins used to analyze heterogenous treatment effects across covariates. (b) Covariate distributions (median + interquartile range) by treatment effect subpopulation bins for variables influencing heterogenous impacts on the landscape.

field samples among these subpopulation bins. We then identified covariates with stronger influences on the yield outcomes of conservation tillage based on covariate distributions within these subpopulations and informed by variable importance rankings for the causal forests (tables 1 and 2).

2.4.2. Analysis of fields following initial tillage conversion

To assess the initial yield impacts from switching tillage practices, we applied the same causal forests approach to the fields we identified as 'single-switch' fields (section 2.3). We conducted one cross-sectional analysis for the final year of yield data for each crop (2017 for maize and 2015 for soybeans) to evaluate the partial treatment effect of each additional year of conservation tillage. Here, the treatment variable was the number of years since adoption, with zero indicating the control case of continued conventional tillage. We then conducted the same analysis on fields that switched from conservation tillage to conventional tillage. We note that the location of fields switching to and from conservation tillage are not similarly distributed in space (see figures S6 and S7), so the spatial support for these analyses is not directly analogous to one another.

2.4.3. Confounders and omitted variables

Socioeconomic factors for which we lacked data can influence adoption, and, if also associated with higher yields, they could cause omitted variable bias in our propensity score and treatment effect estimation. For example, farm size, education, high sales farms, and regulations for highly erodible lands have been positively correlated to conservation tillage adoption [18, 32, 67–70]. Negative correlations exist for farmer age, management by renters, and distance from research stations [32, 68, 69]. Because lower intensity tillage reduces fuel requirements, high fuel costs can also promote adoption [70]. Still, it remains difficult to predict adoption due to a lack of universal features [71, 72], suggesting there is variability in these effects. Nevertheless, the propensity model we developed based upon biophysical factors captures the probability of adoption well (figure S3), and causal forests's doubly robust estimator buffers some misspecification in the propensity score model (section 2.4). Future

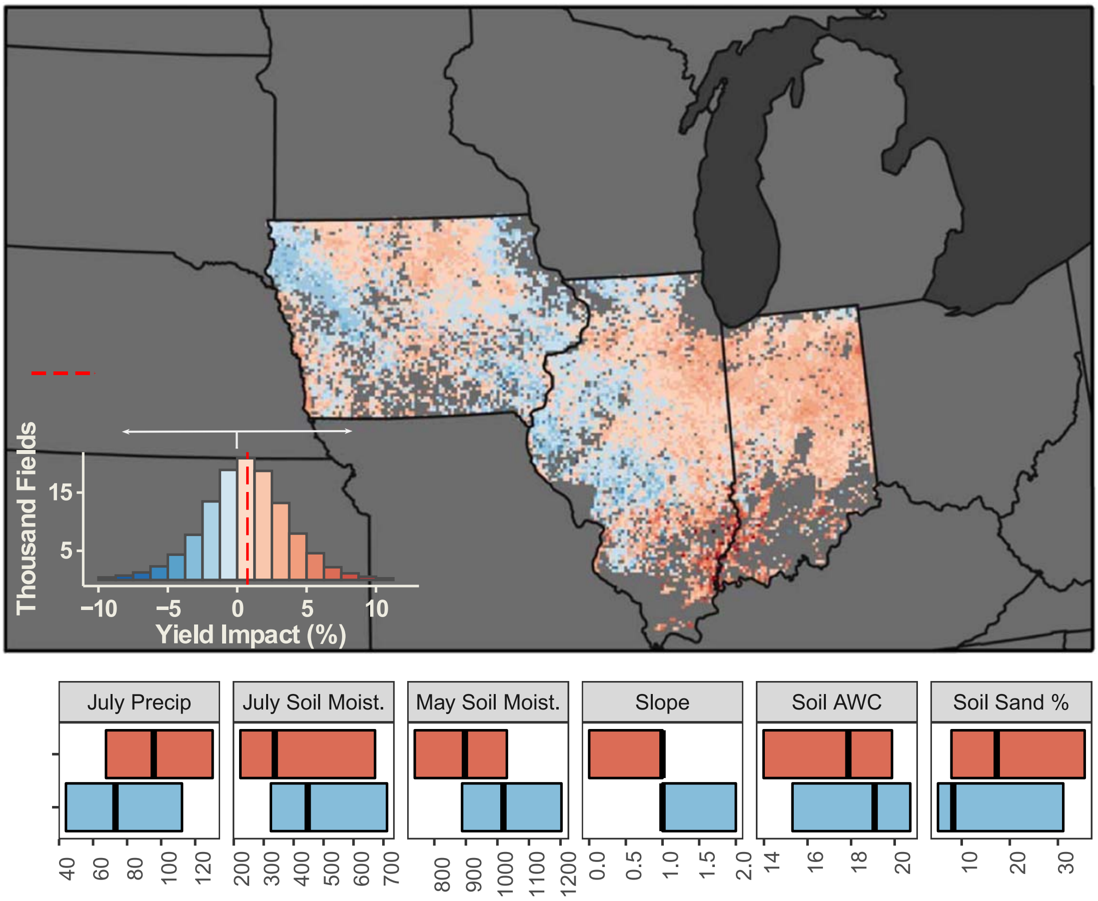

Figure 3. Distribution of soybean yield impacts from conservation tillage from 2005 to 2015. (a) Mean conditional treatment effect for all field-year observations on a regular 5 km^2 grid. The distribution of treatment effects across all 119, 549 field observations is provided in the histogram, with indicators for subpopulation bins used to analyze heterogenous treatment effects across covariates. (b) Covariate distributions (median + interquartile range) by treatment effect subpopulation bins for variables influencing heterogenous impacts on the landscape. AWC = available water content.

large-scale randomized experiments or quasi-natural experiments able to collect data on these attributes would be a useful robustness check for the analysis.

3. Results and discussion

3.1. Biophysical factors associated with conservation tillage

Overall, we found that long-term conservation tillage occurred across a wide range of environmental conditions, as indicated by treatment probabilities above 25% across most covariable values (figure 1(b)). This is consistent with past difficulties identifying universal variables to explain adoption [71, 72]. Field slope ranked highest in importance (table 1), likely explained by greater benefits for erosion relative to flatter fields and policies targeting highly erodible areas [18]. Higher early season temperature, early season precipitation, and July vapor pressure deficits also increased probability of adoption (figure 1(b), table 1), consistent with findings that conservation tillage is often more prominent in warmer, arid conditions [16, 17, 73] and can enhance water infiltration rates [1]. Both soil silt and available water content were positively related to conservation tillage while sand content was negatively correlated (figure 1(b)), although soil variables did not rank high in variable importance.

3.2. Yield effects of long-term conservation tillage

For maize, we found an overall 3.3% yield benefit from conservation tillage (average treatment effect; 95% Confidence Interval, CI = [3.1%, 3.4%]) across fields with long-term tillage practices from 2008 to 2017. This translated to an average yield boost of 0.36 t/ha (CI = [0.34, 0.37]). For soybeans, we found a smaller yield benefit of 0.74% (CI = 0.53%, 0.95%) or 0.024 t/ha (CI = 0.017, 0.031) from 2005 to 2015 within Indiana, Illinois, and Iowa. Generally, these effects are smaller than typical year-to-year yield variability in this region (figure S2) and similar in magnitude to previous plot level work [20, 21, 27, 74, 75]. We did, however, find more evidence for positive yield impacts across the region than the majority of existing literature [16]. This may reflect ongoing technology improvements for conservation tillage implementation [29] or additional insight afforded through our methodology, which allows the inclusion of a large range of covariates and leverages thousands of fields across a wide region.

Tests for treatment effect heterogeneity were significant for both maize ($p < 0.0001$) and soybeans ($p < 0.0001$), indicating treatment effects are moderated by the weather, soil, and slope covariates used. For maize, the 5th–95th percentiles of these conditional average treatment effects (CATEs) ranged from −1.3% to 8.1%; for soybeans, they ranged from −4.7% to 5.8%.

To understand how this heterogeneity manifested across the Corn Belt, we mapped the mean CATE for all field-years on a 5 km^2 regular grid by crop type (figures 2(a) and 3(a)). For both maize and soybeans, negative impacts from conservation tillage were most pronounced in northwestern Iowa and from southeast Iowa into western Illinois. Conservation tillage largely improved yields from eastern Illinois through Indiana. For maize, Ohio, South Dakota, and the outer regions of the Corn Belt displayed strong positive effects. Notably, we found that conservation tillage had a largely positive effect on maize yields in the northern Corn Belt, where it has historically been more limited in practice (figure 1(a)). While it is possible this effect is driven by early adopters inordinately adept at managing their fields, recent studies in Minnesota [29, 76], New York [12], and Canada [32] provide increasing evidence for conservation tillage interest and feasibility in these more northerly latitudes.

3.3. Soils and annual weather moderate yield impact

To understand the underlying biophysical features driving these patterns, we explored conditional treatment effects by field attributes for both maize (figure 2(b)) and soybeans (figure 3(b)). Overall, the soil water balance and seasonal temperatures seem to drive much of the heterogeneity observed. For example, maize and soybean yield benefits were greater than average when baseline late-season (July–August) soil moisture was low, suggesting higher differential success in arid conditions likely due to improved soil water holding capacity. Similarly, soybean field-years with positive yield effects tended to have lower baseline soil available water content from static soil maps, indicating potential improvement in water capacities on these fields from conservation tillage.

In addition to these arid conditions generally thought to benefit from conservation tillage [16], we also found evidence that conservation tillage can improve yields under wet conditions. Soybean field-years with positive yield impacts had higher median July precipitation (figure 3(b)). Similarly, maize field-years with the greatest treatment effects experienced higher median early season precipitation (figure 2(b)). Together, this suggests improved water infiltration on fields under conservation tillage.

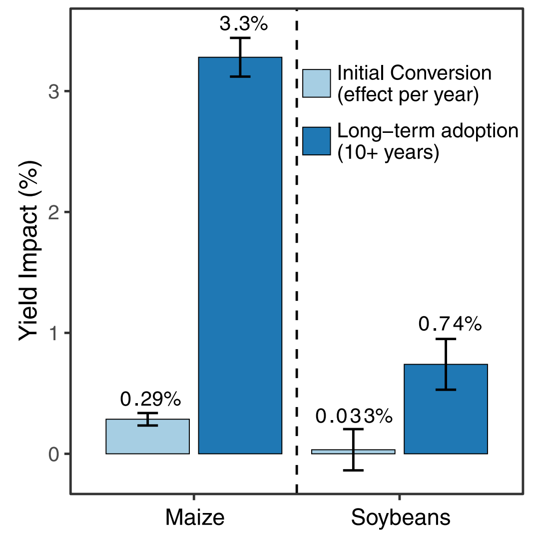

Figure 4. Summary of the average yield impacts of conservation tillage by implementation duration. Dark bars represent long-term tillage management in fields that had consistent tillage classification from 2005 to 2016. Light bars represent fields which switched to conservation tillage during this study period, with years since conversion ranging from 1 to 8. Error bars denote 95% confidence intervals.

On the other hand, we also found evidence that very wet early season soils (April–May) can reduce conservation tillage benefits in both crops. Conventional tillage helps dry water-logged soils [77], often enabling earlier planting dates and thus better yields. Interestingly, conservation tillage performed worse for maize when mean May minimum temperature was higher (figure 2(b)). Although higher temperatures should help dry soils near planting, higher May temperatures could also facilitate weed growth that can compete with maize emergence or, combined with residue cover, increase disease pressure by fostering disease organisms.

Although higher field slopes increased the likelihood of conservation tillage (figure 1(b)), yields were not better on higher slopes for either crop (figures 2(b), 3(b)), possibly because impacts from soil erosion operate on centennial time scales not yet manifested here. However, we were unable to compare fields with slopes higher than 3 degrees due to lack of overlap between tillage types, since high sloped fields had high probabilities of treatment (figures 1(b), section 2.4.1).

3.4. Initial yield impacts from switching tillage practices

There is strong evidence that any benefits from conservation tillage can be absent upon initial implementation and accrue over time as soil health and management improves [16]. For maize and soybeans, we found an overall positive yield effect of 0.29% and 0.033%, respectively, for each additional year under conservation tillage when considering fields between 1 and 8 years since adoption. Although still positive, these effects are an order of magnitude smaller than fields with long-term conservation tillage (figure 4).

These numbers imply that, on average, the full yield benefit of long-term conservation tillage is achieved after 11 years for maize and 22 years for soybeans. Interestingly, we found similar (maize) or greater (soybeans) yield improvements when analyzing fields that switched from conservation tillage to conventional tillage (maize: 0.26%; soy: 0.61%). This suggests that management challenges persist for conservation tillage, likely related to weed control or timing of planting. Indeed, a previous analysis found that in the US circa 2012, less than half of farmers reporting 'no-till' methods practiced them continuously during the previous four years [18]. Because soil benefits are greatest under sustained conservation tillage, there is still a need for improved understanding of these management decisions and challenges.

4. Conclusions

By applying causal inference methods to Earth observation datasets, we found that long-term conservation tillage typically has a small positive yield effect for both maize and soybeans across tens of thousands of fields in the US Corn Belt. This effect is diminished on fields that recently switched from conventional to conservation tillage, supporting the notion that it can take several years to achieve yield benefits due to a time lag in soil response and the learning curve for effective management [16]. Compared with background yield variability from annual weather patterns, cultivars, and management practices in this system, these yield effects are small and would be difficult to detect with localized experiments on small sample sizes. Our satellite-based approach allows us to pool the experience of over 150 000 field observations, improving the ability to detect this signal amid other variation.

Given these rare or minor yield penalties, our results support an emerging consensus that tillage adoption decisions can focus on factors other than yields in this region [20, 75]. In addition to positive effects on soil quality, conservation tillage is typically associated with lower production costs due to reduced machinery, fuel, and labor requirements [1, 24, 78]. Conservation tillage can also reduce supplemental water requirements [27] and field fallowing frequency, enabling increased crop production over time [78]. These savings often counterbalance yield penalties in more marginal areas [27]. In other cases, conservation tillage can have unclear or negative effects. Improved soil carbon storage and reduced NO_2 emissions are sometimes heralded as a benefit of conservation tillage, but study findings are mixed [4, 16, 28, 30]. Similarly, although conservation tillage can reduce surface runoff, accumulated P in the soil can result in high P runoff during storm events that impacts downstream water quality [79]. Ultimately, conservation tillage systems reduce soil erosion, often returning soil loss rates to background levels on par with natural soil generation [2].

Our assessment compares on-the-ground, production-scale fields at a systems level. It is generally understood that a suite of management changes are associated with reduced tillage. We provide evidence that conservation tillage systems are capable of achieving modest yield improvements, but we are unable to attribute yield gains to specific components of any management regime. For this reason, complementary large-scale or quasi-natural experiments with detailed management data would be useful to characterize best management practices. Our results support soil conservation practices by demonstrating that conservation tillage can be used with minimal and typically positive yield impacts under what are likely a set of optimized management practices.

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Data availability statement

Data and code necessary to support the findings of this study and reproduce the analyses and figures is available at https://doi.org/10.5281/zenodo.3525346 and https://doi.org/10.5281/zenodo.3525359, respectively. This includes the field-level samples derived from the annual tillage and yield map datasets, along with associated covariates. Due to privacy concerns, field locations are reported by county only (latitude and longitude have been removed), and the input map datasets are not publicly available.

ORCID iDs

Jillian M Deines https://orcid.org/0000-0002-4279-8765
Sherrie Wang https://orcid.org/0000-0002-4618-5675
David B Lobell https://orcid.org/0000-0002-5969-3476

References

[1] Hobbs P R, Sayre K and Gupta R 2008 The role of conservation agriculture in sustainable agriculture *Phil. Trans. R. Soc.* B **363** 543–55
[2] Montgomery D R 2007 Soil erosion and agricultural sustainability *Proc. Natl Acad. Sci.* **104** 13268–72
[3] Schmidt R, Gravuer K, Bossange A V, Mitchell J and Scow K 2018 Long-term use of cover crops and no-till shift soil microbial community life strategies in agricultural soil *PLoS One* **13** 1–19

[4] Büchi L *et al* 2017 Long and short term changes in crop yield and soil properties induced by the reduction of soil tillage in a long term experiment in Switzerland *Soil Tillage Res.* **174** 120–9
[5] Oldeman L R 1994 The global extent of soil degradation *Soil Resilience and Sustainable Land Use* ed D J Greenland and I Szabolcs (Oxfordshire: CAB International) pp 99–118
[6] Pimentel D *et al* 1995 Environmental and economic costs of soil erosion and conservation benefits *Science* **267** 1117–23
[7] Campbell J E, Lobell D B, Genova R C and Field C B 2008 A global potential of bio-energy on abandoned agricultural land *Environ. Sci. Technol.* **42** 5791–4
[8] Gibbs H K and Salmon J M 2015 Mapping the world's degraded lands *Appl. Geogr.* **57** 12–21
[9] Carter M R 2005 Conservation tillage *Encyclopedia of Soils in the Environment* ed D Hillel (Amsterdam : Elsevier) pp 306–11
[10] Bottinelli N *et al* 2017 Tillage and fertilization practices affect soil aggregate stability in a Humic Cambisol of Northwest France *Soil Tillage Res.* **170** 14–7
[11] Dairon R, Dutertre A, Tournebize J, Marks-Perreau J and Carluer N 2017 Long-term impact of reduced tillage on water and pesticide flow in a drained context *Environ. Sci. Pollut. Res.* **24** 6866–77
[12] Nunes M R, van Es H M, Schindelbeck R, Ristow A J and Ryan M 2018 No-till and cropping system diversification improve soil health and crop yield *Geoderma* **328** 30–43
[13] Derpsch R *et al* 2014 Why do we need to standardize no-tillage research? *Soil Tillage Res.* **137** 16–22
[14] Derpsch R, Friedrich T, Kassam A and Hongwen L 2010 Current status of adoption of no-till farming in the world and some of its main benefits *Int. J. Agric. Biol. Eng.* **3** 1–25
[15] Kassem A, Friedrich T, Derpsch R and Kienzle J 2015 Overview of the worldwide spread of conservation agriculture *F. Actions Sci. Rep.* **8** 0–11
[16] Pittelkow C M *et al* 2015 When does no-till yield more? A global meta-analysis *Field Crops Res.* **183** 156–68
[17] Kurkalova L, Kling C and Zhao J 2006 Green subsidies in agriculture: estimating the adoption costs of conservation tillage from observed behavior *Can. J. Agric. Econ.* **54** 247–67
[18] Wade T and Claasen R 2017 Modeling no-till adoption by corn and soybean producers: insights into sustained adoption *J. Agric. Appl. Econ.* **49** 186–210
[19] Toliver D K *et al* 2012 Effects of no-till on yields as influenced by crop and environmental factors *Agron. J.* **104** 530–41
[20] Daigh A L M *et al* 2018 Yields and yield stability of no-till and chisel-plow fields in the Midwestern US Corn Belt *Field Crops Res.* **218** 243–53
[21] Sindelar A J, Schmer M R, Jin V L, Wienhold B J and Varvel G E 2015 Long-term corn and soybean response to crop rotation and tillage *Agron. J.* **107** 2241–52
[22] Rusinamhodzi L *et al* 2011 A meta-analysis of long-term effects of conservation agriculture on maize grain yield under rain-fed conditions *Agron. Sustain. Dev.* **31** 657–73
[23] DeFelice M S, Carter P R and Mitchell S B 2006 Influence of tillage on corn and soybean yield in the United States and Canada *Crop Manage.* **5**
[24] Al-Kaisi M M, Archontoulis S V, Kwaw-Mensah D and Miguez F 2015 Tillage and crop rotation effects on corn agronomic response and economic return at seven iowa locations *Agron. J.* **107** 1411–24
[25] Pedersen P and Lauer J G 2003 Soybean agronomic response to management systems in the Upper Midwest *Agron. J.* **95** 1146–51
[26] Rattalino Edreira J I *et al* 2017 Assessing causes of yield gaps in agricultural areas with diversity in climate and soils *Agric. Forest Meteorol.* **247** 170–80
[27] Grassini P *et al* 2015 Soybean yield gaps and water productivity in the western US Corn Belt *Field Crops Res.* **179** 150–63
[28] Behnke G D, Zuber S M, Pittelkow C M, Nafziger E D and Villamil M B 2018 Long-term crop rotation and tillage effects on soil greenhouse gas emissions and crop production in Illinois, USA *Agric. Ecosyst. Environ.* **261** 62–70
[29] Daigh A L M *et al* 2019 Crop and soil responses to on-farm conservation tillage practices in the upper midwest *Agric. Environ. Lett.* **4** 90012
[30] Soane B D *et al* 2012 No-till in northern, western and south-western Europe: a review of problems and opportunities for crop production and the environment *Soil Tillage Res.* **118** 66–87
[31] Pittelkow C M *et al* 2015 Productivity limits and potentials of the principles of conservation agriculture *Nature* **517** 365–8
[32] Davey K A and Furtan W H 2008 Factors that affect the adoption decision of conservation tillage in the Prairie region of Canada *Can. J. Agric. Econ.* **56** 257–75
[33] Lobell D B, Thau D, Seifert C, Engle E and Little B 2015 A scalable satellite-based crop yield mapper *Remote Sens. Environ.* **164** 324–33
[34] Jin Z, Azzari G and Lobell D B 2017 Improving the accuracy of satellite-based high-resolution yield estimation: a test of multiple scalable approaches *Agric. Forest Meteorol.* **247** 207–20
[35] Azzari G *et al* 2019 Satellite mapping of tillage practices in the North Central US region from 2005 to 2016 *Remote Sens. Environ.* **221** 417–29
[36] Lobell D B and Azzari G 2017 Satellite detection of rising maize yield heterogeneity in the US Midwest *Environ. Res. Lett.* **12** 014014
[37] Athey S and Wager S 2019 Estimating treatment effects with causal forests: an application (arXiv:1902.07409v1 [stat.ME]) 1–15
[38] Wager S and Athey S 2018 Estimation and inference of heterogeneous treatment effects using random forests *J. Am. Stat. Assoc.* **113** 1228–42
[39] Athey S, Tibshirani J and Wager S 2019 Generalized random forests *Ann. Stat.* **47** 1179–203
[40] Green T R, Kipka H, David O and McMaster G S 2018 Where is the USA Corn Belt, and how is it changing? *Sci. Total Environ.* **618** 1613–8
[41] USDA 2016 *World agricultural suppy and demand estimates*
[42] Peel M, Finlayson B and McMahon T 2007 Updated world map of the Köppen–Geiger climate classification *Hydrol. Earth Syst. Sci.* **11** 1633–44
[43] NASS. Quick Stats API 2019 *USDA National Agricultural Statistics Service* (https://quickstats.nass.usda.gov/api) (Accessed: 1 June 2019)
[44] NRCS 2007 *National Resources Inventory: Soil erosion on cropland* (USDA National Resources Conservation Service)
[45] Boryan C, Yang Z, Mueller R and Craig M 2011 Monitoring US agriculture: the US department of agriculture, national agricultural statistics service, cropland data layer program *Geocarto Int.* **26** 341–58
[46] Wade T, Claassen R and Wallander S 2015 Conservation-practice adoption rates vary widely by crop and region *USDA-ERS Econ. Inf. Bull.* 147
[47] Seifert C A, Azzari G and Lobell D B 2018 Satellite detection of cover crops and their effects on crop yield in the Midwestern United States *Environ. Res. Lett.* **13** 064033
[48] Cohen A A B, Seifert C A, Azzari G and Lobell D B 2019 Rotation effects on corn and soybean yield inferred from satellite and field-level data *Agron. J.* **111** 1–9
[49] Daly C *et al* 2008 Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States *Int. J. Climatol.* **28** 2031–64
[50] Daly C, Smith J I and Olson K V 2015 Mapping atmospheric moisture climatologies across the conterminous United States *PLoS One* **10** e0141140
[51] USGS. National Elevation Dataset 2012 *US Geological Survey*
[52] NRCS. SSURGO Web Soil Survey 2016 *USDA Natural Recources Conservation Service*
[53] Abatzoglou J T 2013 Development of gridded surface meteorological data for ecological applications and modelling *Int. J. Climatol.* **33** 121–31
[54] Abatzoglou J T, Dobrowski S Z, Parks S A and Hegewisch K C 2018 TerraClimate, a high-resolution global dataset of

monthly climate and climatic water balance from 1958 to 2015 *Sci. Data* **5** 1–12
[55] Gorelick N *et al* 2017 Google Earth Engine: planetary-scale geospatial analysis for everyone *Remote Sens. Environ.* **202** 18–27
[56] Breiman L 2001 Random forests *Mach. Learn.* **45** 5–32
[57] Athey S and Imbens G 2016 Recursive partitioning for heterogeneous causal effects *Proc. Natl Acad. Sci.* **113** 7353–60
[58] Belgiu M and Drăgu L 2016 Random forest in remote sensing: a review of applications and future directions *ISPRS J. Photogramm. Remote Sens.* **114** 24–31
[59] Strittmatter A 2019 What is the value added by using causal machine learning methods in a welfare experiment evaluation? (arXiv:1812.06533v2 [econ.EM])
[60] Farbmacher H, Kogel H and Spindler M 2019 Heterogeneous effects of poverty on cognition (http://www.farbmacher.de/working_papers/Farbmacher_etal_2019.pdf)
[61] Robins J M and Rotnitzky A 1995 Semiparametric efficiency in multivariate regression models with missing data *J. Am. Stat. Assoc.* **90** 122–9
[62] Rosenbaum P R and Rubin D B 1983 The central role of the propensity score in observational studies for causal effects *Biometrika* **70** 41–55
[63] Scharfstein D O, Rotnitzky A and Robins J M 1999 Adjusting for nonignorable drop-out using semiparametric nonresponse nodels *J. Am. Stat. Assoc.* **94** 1121–46
[64] Tibshirani J *et al* 2018 grf: generalized random forests (beta) (https://CRAN.R-project.org/package=grf)
[65] R Core Team 2017 R: A language and environment for statistical computing (R Foundation for Statistical Computing) (https://www.R-project.org/)
[66] Strobl C, Boulesteix A-L, Kneib T, Augustin T and Zeileis A 2008 Conditional variable importance for random forests *BMC Bioinf.* **9** 307
[67] Lambert D M, Sullivan P, Claassen R and Foreman L 2007 Profiles of US farm households adopting conservation-compatible practices *Land Use Policy* **24** 72–88
[68] Soule M 2001 Soil management and the farm typology: do small family farms manage soil and nutrient resources differently than large family farms? *Agric. Resour. Econ. Rev.* **30** 179–88
[69] Soule M J, Tegene A and Wiebe K D 2000 Land tenure and the adoption of conservation practices *Am. J. Agric. Econ.* **82** 993–1005
[70] Perry E D, Moschini G C and Hennessy D A 2016 Testing for complementarity: glyphosate tolerant soybeans and conservation tillage *Am. J. Agric. Econ.* **98** 765–84
[71] Knowler D and Bradshaw B 2007 Farmers' adoption of conservation agriculture: a review and synthesis of recent research *Food Policy* **32** 25–48
[72] Yoder L, Ward A S, Dalrymple K, Spak S and Lave R 2019 An analysis of conservation practice adoption studies in agricultural human-natural systems *J. Environ. Manage.* **236** 490–8
[73] Wade T, Kurkalova L and Secchi S 2016 Modeling field-level conservation tillage adoption with aggregate choice data *J. Agric. Resour. Econ.* **41** 266–85
[74] Obrycki J F, Kovar J L, Karlen D L and Birrell S J 2018 Ten-year assessment encourages no-till for corn grain and stover harvest *Agric. Environ. Lett.* **3** 180034
[75] Karlen D L, Kovar J L, Cambardella C A and Colvin T S 2013 Thirty-year tillage effects on crop yield and soil fertility indicators *Soil Tillage Res.* **130** 24–41
[76] Bohman B J *et al* 2018 Groundwater and agriculture: insights from farmers in central Minnesota on how to protect both *J. Soil Water Conserv.* **73** 122A–7A
[77] Morris N L, Miller P C H, Orson J H and Froud-Williams R J 2010 The adoption of non-inversion tillage systems in the United Kingdom and the agronomic impact on soil, crops and the environment-a review *Soil Tillage Res.* **108** 1–15
[78] Triplett G B and Dick W A 2008 No-tillage crop production: a revolution in agriculture! *Agron. J.* **100** 153–65
[79] Kelly P T, Renwick W H, Knoll L and Vanni M J 2019 Stream nitrogen and phosphorus loads are differentially affected by storm events and the difference may be exacerbated by conservation tillage *Environ. Sci. Technol.* **53** 5613–21
[80] Yan L and Roy D P 2016 Conterminous United States crop field size quantification from multi-temporal Landsat data *Remote Sens. Environ.* **172** 67–86