

Climate resilience from long-term low till adoption in US farms

Yuchi Ma¹, David B. Lobell^{1*}

¹Department of Earth System Science and Center on Food Security and the Environment,
Stanford University, USA

*Corresponding author. Email: dlobell@stanford.edu

Oct 2026

Abstract: Low-intensity tillage (low till) has expanded rapidly in the United States since 2000. Evidence on its yield impacts has come mainly from field experiments and has been limited to short time horizons. Using satellite-based observations from >40 million field-year pairs across the U.S. Corn Belt from 1999-2023, we demonstrate that yield gains continue to accrue with longer duration of low-till adoption, by 0.20% yr⁻¹ for corn and 0.16% yr⁻¹ for soybean, and that yield benefits are greater in hot and dry growing-season conditions. A re-occurrence of the 2012 drought would have significantly smaller impacts if it occurred today, when more than 40% of fields have 10+ years of low-till, and sustained low-till management to 2035 could offset one-third to one-half of projected yield losses from climate change.

The paper is a non-peer-reviewed preprint submitted to EarthArXiv.

Introduction

As climate change intensifies the stresses faced by crops in many regions (1), agricultural systems must adapt in ways that improve climate resilience, reduce environmental footprints, and sustain productivity. Proposed agricultural conservation practices are often able to advance some of these goals but struggle to achieve all three (2). For example, organic farming can reduce synthetic fertilizer and pesticide use but often incurs yield penalties relative to conventional systems (3). Likewise, cover cropping can reduce erosion and improve soil health, but may reduce subsequent crop yields (4).

Low-intensity tillage (low till) is a conservation practice that has been increasingly adopted in many regions of the world since 1980 (5, 6). For centuries, high-intensity tillage (high till) was widely used to prepare seedbeds by inverting topsoil, incorporating surface crop residues, suppressing weeds, and loosening compacted soil layers (7). In low till systems, by contrast, soil disturbance is minimized by using low-intensity techniques (e.g., strip till or no till) and leaving at least 30% of crop residues on the surface (8, 9), which protects the soil from erosion (10), improves water retention (11), supports soil structure (12), and reduces greenhouse gas emissions (7). These benefits have made low till an important component of efforts to build more resilient and sustainable agricultural systems. For example, the United States Department of Agriculture (USDA) conservation programs provide roughly \$6.5-7.5 billion annually in financial and technical assistance to support conservation on U.S. farms, and low till was among the top two funded categories in 1998-2016 (13).

However, low-till systems are not without controversy. They have often been accompanied by greater reliance on herbicides, especially glyphosate, raising concerns about resistant weeds, chemical dependence, and associated impacts on human health (14, 15). These competing benefits and costs make it essential to understand the productivity consequences of low-disturbance farming systems. Yet the yield effects of low-till adoption remain unresolved, particularly over long time horizons and across varying weather conditions (16–18). Much of the existing literature relies either on experiments conducted at research stations, or on cross-sectional comparisons across fields, farms, or locations (16, 18, 19). Such comparisons are informative but cannot fully account for the fact that farmers do not adopt low till randomly. Adoption may be shaped by underlying differences in soils, climate, crop choice, management intensity, or producer characteristics that also affect yields. As a result, observed yield differences between low-till and high-till fields may reflect not only the effect of tillage itself, but also pre-existing differences between adopters and non-adopters.

A second gap in the literature is that most studies evaluate low-till systems over relatively short time horizons, with a median experimental duration of under five years (17, 20, 21). This is important because the agronomic benefits of low-till adoption, especially those linked to improvements in soil structure, organic matter, and water-holding capacity, often accumulate gradually and may take years to fully emerge (22, 23). Statistically significant but negative yield effects could appear in short-term low-till adoption (less than 10 years), in direct contradiction to the long-term positive pattern (22). Studies based on short-duration adoption may therefore understate the long-run benefits of low-till practices or mischaracterize its yield effects during the transition period, when soils and management systems are still adjusting (24). Better evidence is needed to understand how the effects of low-till adoption evolve over time and whether short-run outcomes differ from longer-run impacts.

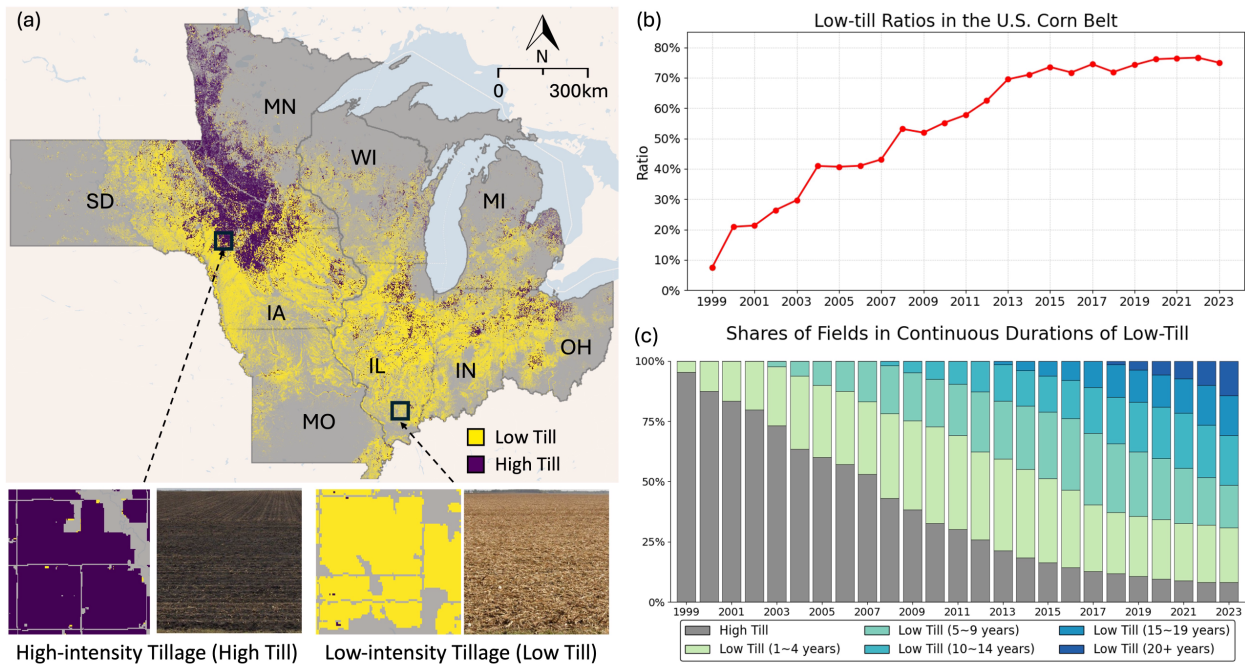


Fig 1. The rise of low till in the U.S. (a) An example satellite-based tillage map for 2017 in the study area, which covers 9 states in the U.S. Corn Belt: Illinois (IL), Indiana (IN), Iowa (IA), Michigan (MI), Missouri (MO), Minnesota (MN), Ohio (OH), South Dakota (SD), Wisconsin (WI). (b) Average estimated annual rates of low-till adoption in the region, which have increased from 1999 to 2023. (c) Shares of fields with continuous low-till adoption for different durations, illustrating the growing share of long-term adopters. The durations for cumulative low-till adoption show a similar pattern (Fig S1).

This study addresses these gaps by examining low-till systems in a way that better accounts for both selection and duration. Using a recent satellite-based high-resolution tillage dataset in the U.S. Corn Belt from 1999 to 2023 (Fig 1 (a)) (25), we evaluate the relationship between durations of low-till adoption and yield outcomes for corn and soybean across over 40 million field-year records in the U.S. Midwest. Croplands in this region are mostly rain-fed and have experienced significant increase in low-till adoption ratios during the study period, with increasing shares of fields with long-term adoption (Fig 1 (b)–(c)). For example, at the time of the major 2012 drought, less than 25% of low-till adopters had been using the practice for more than 10 years, whereas by 2023 over 50% had reached this milestone.

We focus on the within-field dynamics using a two-way fixed effects (TWFE) model (Fig 2), with field fixed effects accounting for differences between early adopters, late adopters, and non-adopters that may confound simple cross-sectional comparisons, and year fixed effects accounting for the general increase in yields over time (most of which is unrelated to low-till adoption). We estimate a model that is linear in years since adoption as well as a model with specific bins of time since adoption, to explicitly test whether and how the effects of low-till adoption strengthen over time as soil improvements accumulate. Only rain-fed fields are considered in this study, by removing any locations that had irrigation at any point in the study period (26).

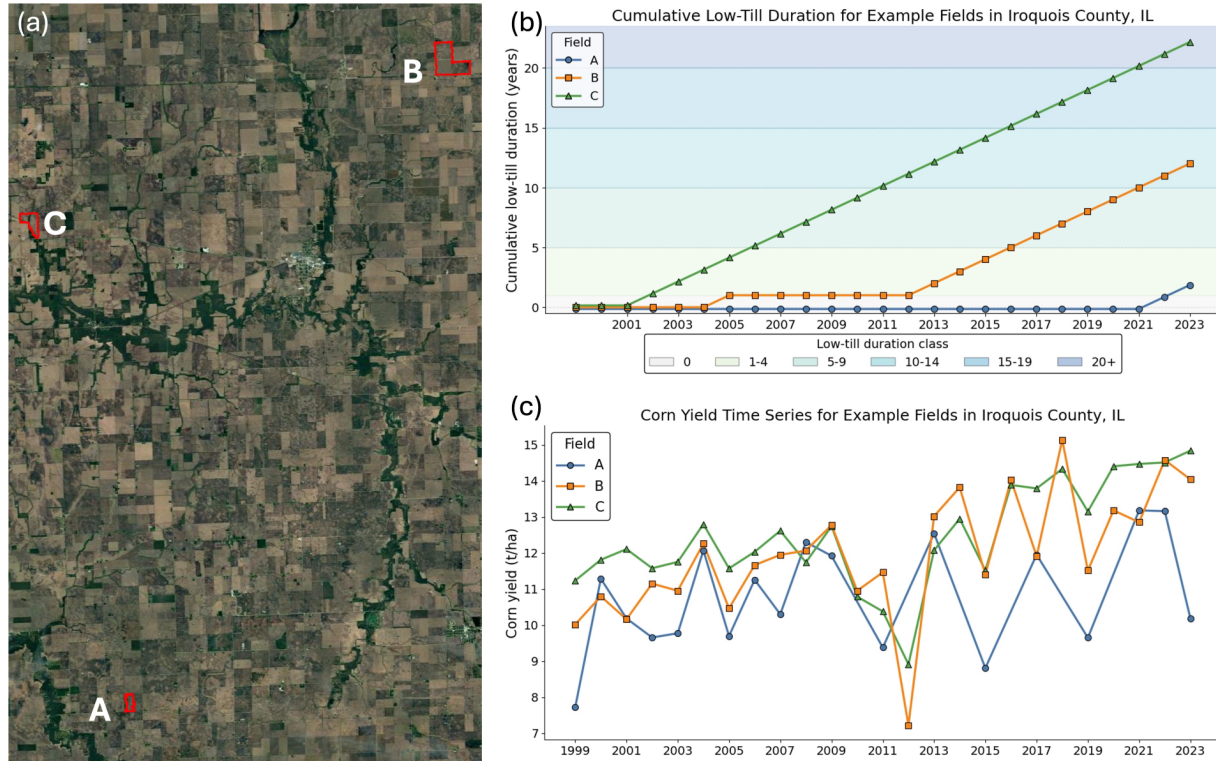


Fig 2. **Field identification strategy.** (a) Three example fields with different durations of low till in Iroquois County, Illinois (IL). (b) Field A remained under high till from 1999 through 2021, then switched to low till in 2022. Field B switched to low till in 2005, reverted in subsequent years, and then remained under low till from 2013 onward. Field B's records after 2005 would be removed for continuous duration models but included in the cumulative duration models. Field C adopted low till in 2002 and maintained it thereafter. (c) The corresponding corn yield time series for each example field. Our model related yields to low-till duration, accounting for unobserved time-invariant differences between fields by using field fixed-effects.

Results

Crop yields rise with longer periods of low till

Roughly a quarter of fields that adopted low till during the study period maintained the practice every year after adoption. For these “continuous” low-till fields, we find that yields exhibit clear and increasing benefits with longer periods of low till (Fig 3 (a)&(c)). Corn yields increase by $0.20\% \text{ yr}^{-1}$ following the adoption of low till (CI: $0.15\text{--}0.25\% \text{ yr}^{-1}$) and soybean exhibits a smaller but still positive response, increasing by $0.16\% \text{ yr}^{-1}$ after low-till adoption (CI: $0.12\text{--}0.20\% \text{ yr}^{-1}$) (Table S1, S2). Duration-category models (in which low-till treatment duration is grouped into 1–4 years, 5–9 years, etc.) indicate a positive and monotonic association between low-till duration and yields, relative to the omitted reference category (high till). Overall, the linear model and the duration-category model show strong agreement, both suggesting a dose-response pattern in which longer tillage duration is associated with progressively larger increases in the yield outcome.

When we consider all fields, including the roughly three quarters of adopters that revert to high till for one or more years before the end of the period (e.g., Field B in Fig. 2(b)), we find similarly positive effects on yield, albeit slightly reduced for both crops (Fig 3 (b)&(d)). These results indicate that most (but not all) of yield benefits persist even after fields revert from low-till management.

A potential concern with standard TWFE estimators is that, since already-adopting fields serve as controls for later adopters, the estimated effect at any given duration can absorb effects from other durations, distorting the shape of the duration profile (27, 28). We therefore re-estimated the duration profile with the Sun and Abraham (SA) (33) interaction-weighted estimator on never-reverting and never-adopting fields, which aggregates cohort-specific dynamic effects. The SA estimates show long-term adoption effects within 0.05 percentage points of our main estimates for both crops (Fig S6). Notably, the SA estimates also show small and flat effects in the pre-treatment period (Fig S8), indicating that adopters were not already experiencing steeper yield gains prior to treatment.

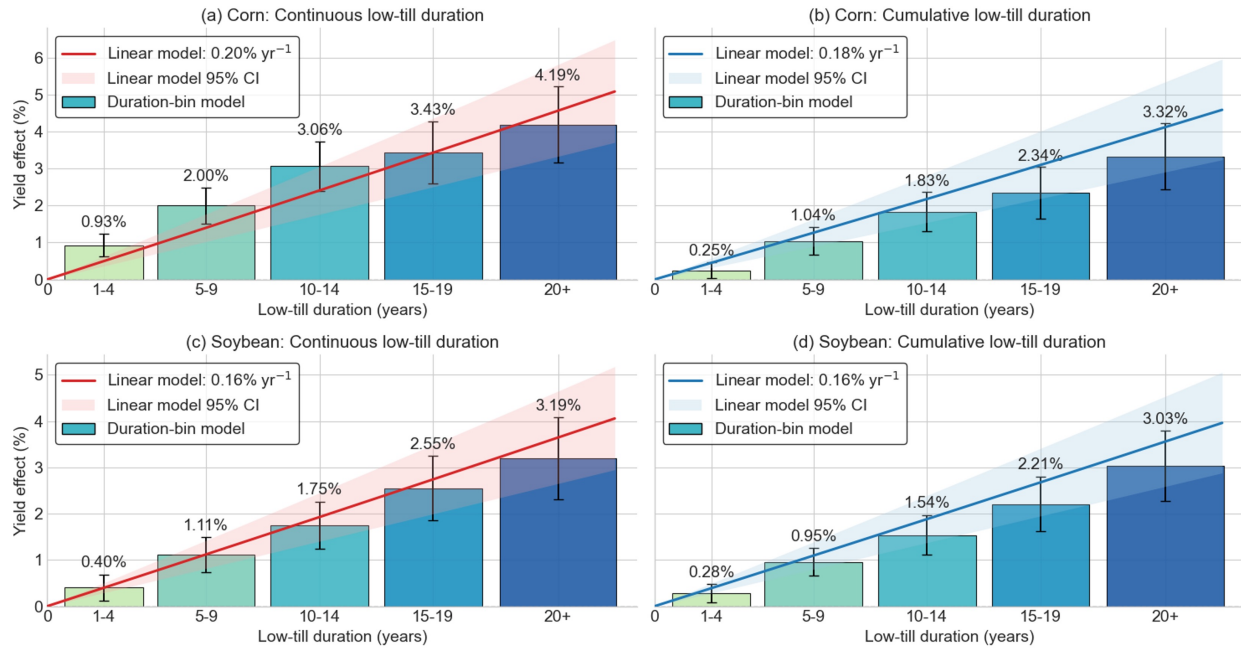


Fig 3. Crop performance rises with longer periods of low-till adoption. The estimated yield effect of low-till adoption by continuous duration models and cumulative duration models for (a-b) corn and (c-d) soybean. All models include field and year fixed effects, are weighted by field area, and have standard errors clustered by county. Error bars denote 95% confidence intervals. The estimates by cumulative duration models (sample size: 44.5M (corn) and 40.3M (soybean)) are lower than those by continuous durations models (sample size: 23.0M (corn) and 20.8M (soybean)) while still maintain an increasing positive yield effects along with the durations, indicating the sustained yield benefits for reverted fields. The summary of coefficients in the panel regression models is provided in Table S1-S6.

Yields benefits of low-till rise in dry and hot conditions

To evaluate how yield effects of continuous low-till systems depend on contemporaneous weather conditions, we build weather-binned models that include interactions between low-till duration and weather, retaining two-way fixed effects for field and year. These models indicate that low-till effects for corn are consistently positive across weather bins, with the strongest responses occurring under low growing-season precipitation (PPT, Jun-Sep) (Fig 4a). The treatment effect (which averaged 0.20% yr⁻¹ of adoption) reaches 0.30% yr⁻¹ in the low-growing-season-PPT bin. Meanwhile, the yield effects in the high-EDD bin also reach 0.30% yr⁻¹, which is significantly higher than its effects in low- and middle-EDD bins. Yield effects conditioned on early spring weather conditions remained relatively stable, with only minor variation across different weather bins (Fig S3(a)). For soybean, yield responses are more heterogeneous and less uniformly beneficial (Fig 4b, Fig S3(b)). Similar to corn, soybean yields exhibit strong benefits of low-till

under high EDD ($0.36\% \text{ yr}^{-1}$, compared to $0.16\% \text{ yr}^{-1}$ on average) and under low growing-season precipitation ($0.24\% \text{ yr}^{-1}$). In contrast, the effects are marginal or statistically insignificant under cooler thermal conditions or in regions with high growing-season precipitation (Fig 4b).

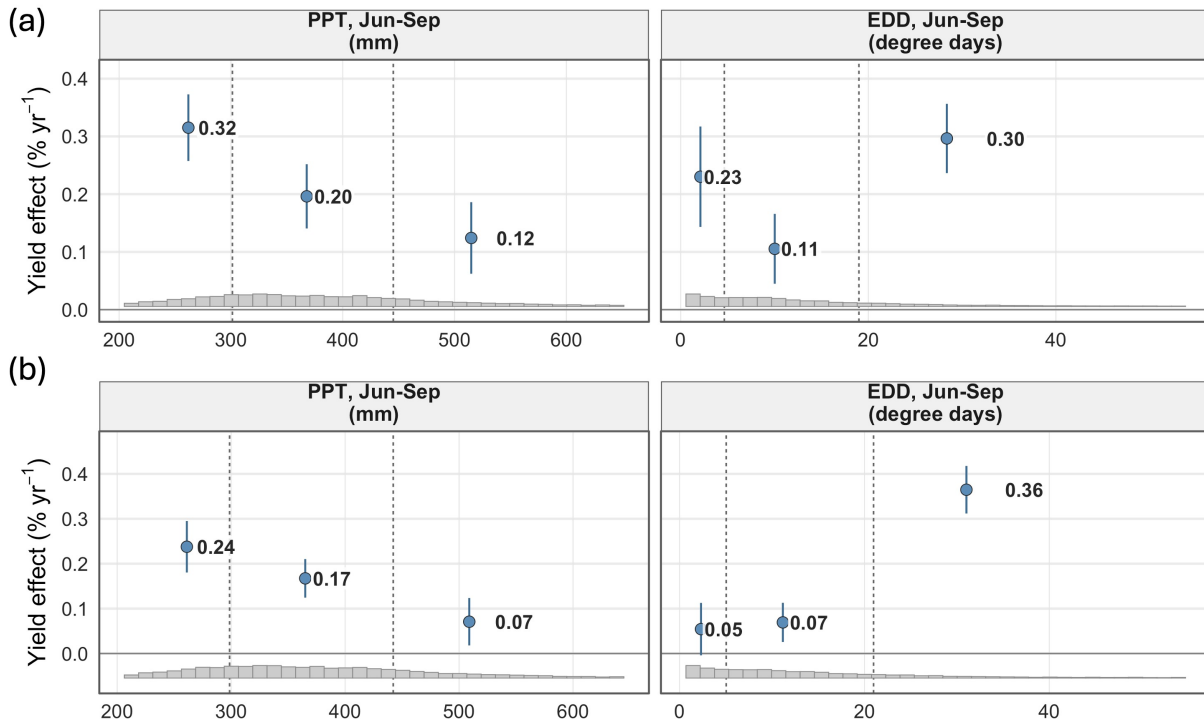


Fig 4. Effects of low-till adoption on yields vary across weather bins. Estimated effect of one additional year of continuous low-till adoption on (a) corn and (b) soybean yields. For each focal weather variable (PPT and EDD, Jun-Sep), observations are assigned to low (bottom quartile), middle (middle half) and high (top quartile) bins, and the remaining weather variables enter additively as controls. In each panel, the focal weather variable defined the bins, and the remaining four weather variables enter additively as linear controls; bin-specific coefficients are evaluated at the median of each bin and plotted at that value. All models include field and year fixed effects, are weighted by field area, and have standard errors clustered by county. Error bars denote 95% confidence intervals, and histograms along the horizontal axis show the distribution of each weather covariate (middle 90% shown). The complete estimated effect for each focal weather variable is provided in Fig S3 and Table S7-S8.

Sustained low-till adoption mitigates yield loss under extreme heat stress

To evaluate the climate adaptation potentials of sustained low-till adoption, we considered two climate scenarios. First, we simulate a historical counterfactual in which 2012 weather (representing the largest drought in recent history) occurred under alternative low-till adoption and duration scenarios (Fig 5a). Under the actual low-till adoption durations as of 2012, the estimated yield losses are 20.0% relative to average yields for corn, and 13.4% for soybean. Both losses are broadly consistent with the reported yield losses of 26% for corn and 9% for soybean during the 2012 heatwave (29), when the growing-season EDD was more than twice the 2010s average while precipitation was 40% lower (Table S9). The climate adaptation effects of low-till systems remained modest in 2012, as the average duration of low-till adoption was only 6 years.

If the 2012 drought had occurred 11 years later, under the actual accumulated durations of low-till adoption in 2023 (the final year of the tillage dataset), the average yield losses would be significantly reduced to 17.5% for corn and 10.3% for soybean (Fig 5a), indicating that the

expansion and maturation of low-till systems would substantially mitigate yield losses under extreme heat conditions. Furthermore, with continued adoption of low-till practices to 2035, the average yield losses under a 2012 scenario are projected to reduce to 14.3% for corn and 6.6% for soybean. Thus, sustained low-till adoption could offset 28.5% and 50.7% of the yield losses caused by a 2012-like heatwave for corn and soybean, respectively, relative to a scenario with limited long-term low-till adoption as of 2012.

As a second scenario, we simulate the impacts of 30 years of climate change to evaluate the adaptation benefits of sustained low-till adoption by the mid-2030s. Under a high-emission scenario (SSP5-8.5), future climate change causes significant yield losses for both corn and soybean relative to a baseline of average weather conditions of the 2000s. However, the extent of this impact depends significantly on low-till adoption duration, a factor ignored in previous climate impact assessments. Specifically, assuming the low-till adoption of the baseline period with an average duration of 2 years, average yield losses are 24.2% for corn and 15.7% for soybean (Fig 5b). These losses are primarily driven by increasing heat stress, with average growing-season EDD projected to rise from 23.15°C-days in 2000s to 51.10°C-days under SSP5-8.5 by the 2030s (Table S9). Continued adoption of low till to the 2030s is projected to substantially mitigate these climate-change-induced yield losses. Under sustained low-till adoption through 2035, more than 80% fields are expected to have more than 20-year low-till adoption. Projected corn yield losses decrease by approximately one-third, from 24.2% to 17.0% under SSP5-8.5. Likewise, projected soybean yield losses are reduced by more than one-half, from 15.7% to 6.7%. Overall, sustained low-till adoption could offset approximately one-third to one-half of the yield losses associated with future climate change, highlighting its strong potential as an effective climate adaptation strategy for both corn and soybean production in U.S. farms.

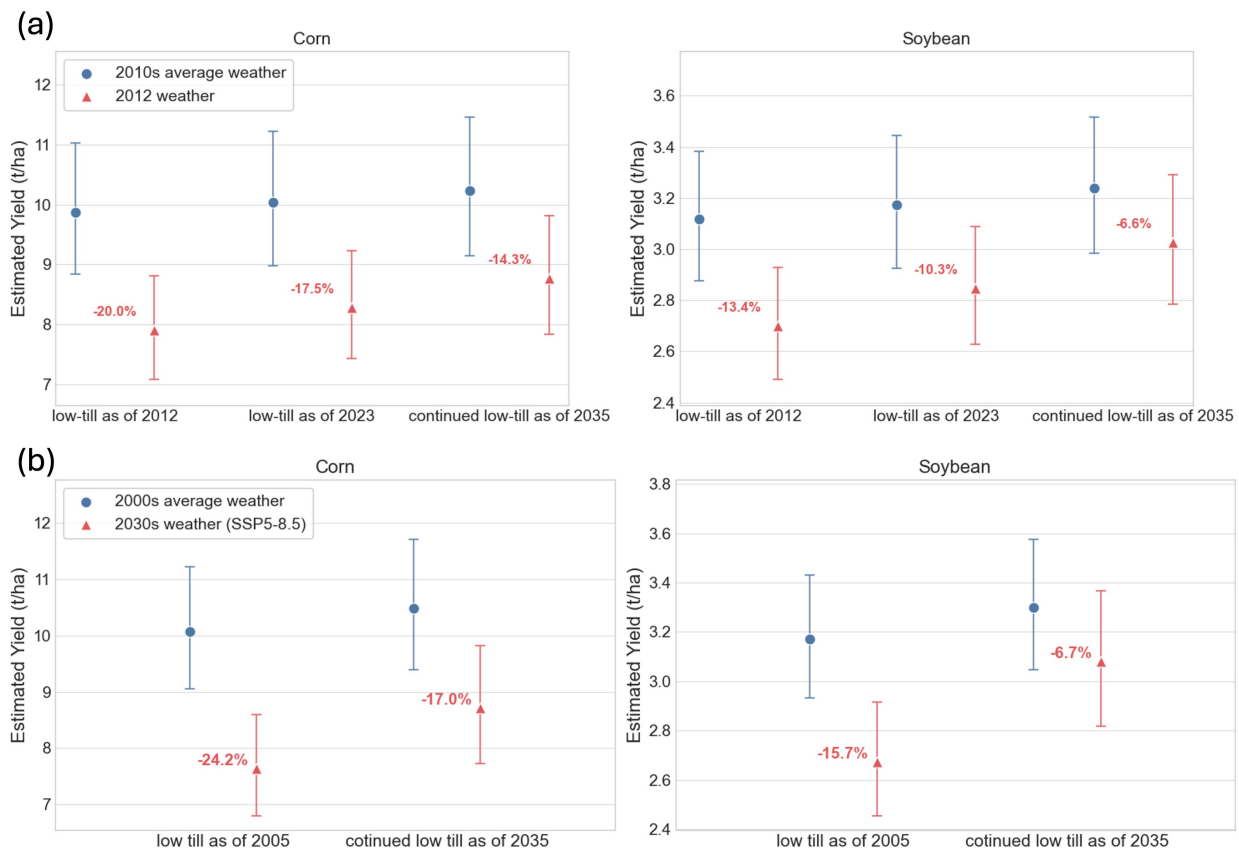


Fig 5. Continued low-till systems mitigate yield losses under both the historical heatwave and the future emission scenarios. Estimated yields based on the EDD-binned models are shown for (a) the 2010s average weather conditions (blue) and the 2012-like heat-exposure counterfactuals (red) and (b) the 2000s average weather conditions (blue) and projected mid-2030s weather conditions under SSP5-8.5 (red). Three low-till adoption and duration patterns are considered in (a), including low-till durations as of 2012, low-till durations as of 2023, and continued low-till durations as of 2035 that assumes all low-till fields in 2023 continue implementing low till through 2035. Two low-till adoption patterns are considered in (b), including low-till durations as of 2005 and continued low-till durations as of 2035. The percentages indicate the yield losses relative to the no-climate-change baseline scenario (blue). Error bars indicate 95% confidence intervals.

Discussion

Evidence on the yield effects of low-till adoption has remained mixed, owing in part to differences in study design, time horizon, and environmental context. Much of the existing literature is based either on field trials conducted under controlled management (18, 30) or on meta-analyses that aggregate experimental results across diverse settings (17, 31, 32). Those approaches have been essential for identifying potential mechanisms, but they provide limited evidence on how low till performs at field scale under real-world management over long periods of continuous adoption.

Our analysis helps fill this gap by linking more than 40 million field-year observation across 25 years to field-level tillage durations, allowing us to estimate the yield consequences of low till under the climatic, agronomic, and operational conditions that farmers actually face. Our findings are broadly consistent with prior observational studies that low till can improve corn and soybean yields (16), particularly in drought environments, but they go further in three important ways. First, we show that the productivity effects of low till are strongly duration dependent and yield gains expand with continued adoption. This indicates that the agronomic benefits of low-till adoption accumulate as soil structure, water retention, and biological activity improve over repeated years of reduced soil disturbance (16, 33). Second, we demonstrate that these gains are systematically larger for corn than for soybean (Fig 3), consistent with corn's greater sensitivity to water and nutrient limitations (34, 35), while we also show soybean benefits become substantial as adoption persists. Third, rather than identifying only average treatment effects, we show that the yield response to low till is highly state dependent, with larger benefits under low precipitation and high extreme degree days during the growing season. Together, these findings suggest that part of the disagreement in the previous literature may reflect variation not only in site conditions, but also in whether studies captured sufficiently long adoption histories and sufficiently stressful weather conditions.

These results also strengthen the case for interpreting low till as a climate adaptation strategy in the U.S. farms rather than solely a soil conservation practice. Previous studies have suggested that low-till systems tend to be more beneficial in arid and hot environments (16, 31, 32, 36) and our results concur with this evidence while providing a 25-year field-scale empirical basis for the conclusion. The adaptation value of low till appears to grow through time as soil improvements accumulate and becomes most visible when crops are exposed to extreme heat and water stress. Our projections that continued adoption through the mid-2030s could offset one-third to one-half of heat-related yield losses under a 2012-like shock and under future warming scenarios suggest that the benefits of low till extend beyond long-run soil sustainability to near-term risk reduction in major rainfed cropping systems in U.S. farms.

These findings have practical implications for climate-smart agriculture and conservation policy. As warming intensifies and precipitation becomes more variable, practices that improve soil water

regulation and reduce sensitivity to drought stress will become increasingly valuable. As the benefits of low till accumulate gradually and are amplified under climate stress, intermittent or short-lived adoption is unlikely to realize its full value. Policies that lower transition costs, support sustained adoption, and help farmers integrate low till with complementary practices such as residue management (37), crop rotations (14), appropriate weed control (6), and specialized planting technologies (38) may therefore yield larger returns than policies focused on one-time adoption alone. More broadly, our results suggest that conservation practices should be evaluated not only by their average effects, but also by how their benefits evolve over time and under increasingly extreme weather.

References

1. D. B. Lobell, W. Schlenker, J. Costa-Roberts, Climate Trends and Global Crop Production Since 1980. *Science* **333**, 616–620 (2011).
2. C. Kremen, A. Miles, Ecosystem Services in Biologically Diversified versus Conventional Farming Systems: Benefits, Externalities, and Trade-Offs. *Ecology and Society* **17**, 40 (2012).
3. V. Seufert, N. Ramankutty, J. A. Foley, Comparing the yields of organic and conventional agriculture. *Nature* **485**, 229–232 (2012).
4. D. B. Lobell, S. Di Tommaso, Q. Zhou, Y. Ma, J. Specht, K. Guan, The mixed effects of recent cover crop adoption on US cropland productivity. *Nat Sustain*, 1–9 (2025).
5. P. R. Hobbs, K. Sayre, R. Gupta, The role of conservation agriculture in sustainable agriculture. *Philos Trans R Soc Lond B Biol Sci* **363**, 543–555 (2007).
6. G. B. Triplett Jr., W. A. Dick, No-Tillage Crop Production: A Revolution in Agriculture! *Agronomy Journal* **100**, S-153-S-165 (2008).
7. C. Lu, Z. Yu, D. A. Hennessy, H. Feng, H. Tian, D. Hui, Emerging weed resistance increases tillage intensity and greenhouse gas emissions in the US corn–soybean cropping system. *Nat Food* **3**, 266–274 (2022).
8. C. S. T. Daughtry, P. C. Doraiswamy, E. R. Hunt, A. J. Stern, J. E. McMurtrey, J. H. Prueger, Remote sensing of crop residue cover and soil tillage intensity. *Soil and Tillage Research* **91**, 101–108 (2006).
9. R. Claassen, M. Bowman, J. McFadden, D. Smith, S. Wallander, Tillage intensity and conservation cropping in the United States. (2018).
10. Y. Sun, Y. Zeng, Q. Shi, X. Pan, S. Huang, No-tillage controls on runoff: A meta-analysis. *Soil and Tillage Research* **153**, 1–6 (2015).
11. Y. Li, Z. Li, S. Cui, S. Jagadamma, Q. Zhang, Residue retention and minimum tillage improve physical environment of the soil in croplands: A global meta-analysis. *Soil and Tillage Research* **194**, 104292 (2019).

12. S. Mondal, D. Chakraborty, Global meta-analysis suggests that no-tillage favourably changes soil structure and porosity. *Geoderma* **405**, 115443 (2022).
13. S. Wallander, M. Elizabeth, Shifts in payments for the top five crop management practices in USDA's Environmental Quality Incentives Program (2019).
<https://www.ers.usda.gov/data-products/charts-of-note/chart-detail?chartId=94846>.
14. N. Colbach, S. Cordeau, Are No-Till Herbicide-Free Systems Possible? A Simulation Study. *Front. Agron.* **4** (2022).
15. E. Reynier, E. Rubin, Glyphosate exposure and GM seed rollout unequally reduced perinatal health. *Proceedings of the National Academy of Sciences* **122**, e2413013121 (2025).
16. J. M. Deines, S. Wang, D. B. Lobell, Satellites reveal a small positive yield effect from conservation tillage across the US Corn Belt. *Environ. Res. Lett.* **14**, 124038 (2019).
17. C. M. Pittelkow, B. A. Linquist, M. E. Lundy, X. Liang, K. J. van Groenigen, J. Lee, N. van Gestel, J. Six, R. T. Venterea, C. van Kessel, When does no-till yield more? A global meta-analysis. *Field Crops Research* **183**, 156–168 (2015).
18. A. L. M. Daigh, W. A. Dick, M. J. Helmers, R. Lal, J. G. Lauer, E. Nafziger, C. H. Pederson, J. Strock, M. Villamil, A. Mukherjee, R. Cruse, Yields and yield stability of no-till and chisel-plow fields in the Midwestern US Corn Belt. *Field Crops Research* **218**, 243–253 (2018).
19. O. Erenstein, R. K. Malik, S. Singh, “Adoption and Impacts of Zero-Tillage in the Rice-Wheat Zone of Irrigated Haryana, India” (2007); <https://doi.org/10.22004/ag.econ.56092>.
20. O. J. Idowu, S. Sultana, M. Darapuneni, L. Beck, R. Steiner, Short-term Conservation Tillage Effects on Corn Silage Yield and Soil Quality in an Irrigated, Arid Agroecosystem. *Agronomy* **9**, 455 (2019).
21. S. Farhangi-Abriz, K. Ghassemi-Golezani, S. Torabian, A short-term study of soil microbial activities and soybean productivity under tillage systems with low soil organic matter. *Applied Soil Ecology* **168**, 104122 (2021).
22. S. Cusser, C. Bahlai, S. M. Swinton, G. P. Robertson, N. M. Haddad, Long-term research avoids spurious and misleading trends in sustainability attributes of no-till. *Global Change Biology* **26**, 3715–3725 (2020).
23. X. Zhao, S.-L. Liu, C. Pu, X.-Q. Zhang, J.-F. Xue, Y.-X. Ren, X.-L. Zhao, F. Chen, R. Lal, H.-L. Zhang, Crop yields under no-till farming in China: A meta-analysis. *European Journal of Agronomy* **84**, 67–75 (2017).
24. H. Blanco-Canqui, S. J. Ruis, No-tillage and soil physical environment. *Geoderma* **326**, 164–200 (2018).

25. Y. Ma, Y. Shen, A. Swatantran, C. Kelly, D. B. Lobell, STaPL: Scale Transfer with Pseudo-Labeling for satellite-based mapping of agricultural practices. *Remote Sensing of Environment* **343**, 115500 (2026).
- 5 26. Y. Xie, T. J. Lark, J. F. Brown, H. K. Gibbs, Mapping irrigated cropland extent across the conterminous United States at 30 m resolution using a semi-automatic training approach on Google Earth Engine. *ISPRS Journal of Photogrammetry and Remote Sensing* **155**, 136–149 (2019).
27. C. de Chaisemartin, X. D’Haultfœuille, Two-Way Fixed Effects Estimators with Heterogeneous Treatment Effects. *American Economic Review* **110**, 2964–2996 (2020).
- 10 28. L. Sun, S. Abraham, Estimating dynamic treatment effects in event studies with heterogeneous treatment effects. *Journal of Econometrics* **225**, 175–199 (2021).
29. B. R. Rippey, The U.S. drought of 2012. *Weather and Climate Extremes* **10**, 57–64 (2015).
- 15 30. L. Büchi, M. Wendling, C. Amossé, B. Jeangros, S. Sinaj, R. Charles, 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 and Tillage Research* **174**, 120–129 (2017).
31. J. Sun, W. Niu, Y. Du, L. Ma, S. Huang, F. Mu, Q. Zhang, G. Li, J. Zhu, K. H. M. Siddique, Regionally adapted conservation tillage reduces the risk of crop yield losses: A global meta-analysis. *Soil and Tillage Research* **244**, 106265 (2024).
- 20 32. Y. Huang, W. Ren, L. Wang, D. Hui, J. H. Grove, X. Yang, B. Tao, B. Goff, Greenhouse gas emissions and crop yield in no-tillage systems: A meta-analysis. *Agriculture, Ecosystems & Environment* **268**, 144–153 (2018).
33. M. R. Nunes, H. M. van Es, R. Schindelbeck, A. J. Ristow, M. Ryan, No-till and cropping system diversification improve soil health and crop yield. *Geoderma* **328**, 30–43 (2018).
- 25 34. W. B. Bruce, G. O. Edmeades, T. C. Barker, Molecular and physiological approaches to maize improvement for drought tolerance. *J Exp Bot* **53**, 13–25 (2002).
- 35 35. A. E. Asibi, Q. Chai, J. A. Coulter, Mechanisms of Nitrogen Use in Maize. *Agronomy* **9**, 775 (2019).
36. C. M. Pittelkow, B. A. Linquist, M. E. Lundy, X. Liang, K. J. van Groenigen, J. Lee, N. van Gestel, J. Six, R. T. Venterea, C. van Kessel, When does no-till yield more? A global meta-analysis. *Field Crops Research* **183**, 156–168 (2015).
- 30 37. M.-S. Turmel, A. Speratti, F. Baudron, N. Verhulst, B. Govaerts, Crop residue management and soil health: A systems analysis. *Agricultural Systems* **134**, 6–16 (2015).
38. Y. Ma, Z. Li, Y. Xu, C. Li, H. Ding, C. Li, Q. Tang, M. Liu, J. Hou, The Development of No-Tillage Seeding Technology for Conservation Tillage—A Review. *Sustainability* **17**, 1808 (2025).
- 35

39. Y. Ma, S.-Z. Liang, D. B. Myers, A. Swatantran, D. B. Lobell, Subfield-level crop yield mapping without ground truth data: A scale transfer framework. *Remote Sensing of Environment* **315**, 114427 (2024).
40. K. Hunt, J. Abernethy, P. Beeson, M. Bowman, S. Wallander, R. Williams, *Crop Sequence Boundaries (CSB): Delineated Fields Using Remotely Sensed Crop Rotations* (2023).
41. C. Boryan, Z. Yang, R. Mueller, M. Craig, Monitoring US agriculture: the US Department of Agriculture, National Agricultural Statistics Service, Cropland Data Layer Program. *Geocarto International* **26**, 341–358 (2011).
42. Y. Xie, H. K. Gibbs, T. J. Lark, Landsat-based Irrigation Dataset (LANID): 30m resolution maps of irrigation distribution, frequency, and change for the US, 1997–2017. *Earth System Science Data* **13**, 5689–5710 (2021).
43. C. Daly, M. Halbleib, J. I. Smith, W. P. Gibson, M. K. Doggett, G. H. Taylor, J. Curtis, P. P. Pasteris, Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology* **28**, 2031–2064 (2008).
44. B. Thrasher, W. Wang, A. Michaelis, F. Melton, T. Lee, R. Nemani, NASA Global Daily Downscaled Projections, CMIP6. *Sci Data* **9**, 262 (2022).
45. J. Hainmueller, J. Mummolo, Y. Xu, How Much Should We Trust Estimates from Multiplicative Interaction Models? Simple Tools to Improve Empirical Practice. *Political Analysis* **27**, 163–192 (2019).

Materials

Tillage type, crop yields, and field boundary datasets

Annual tillage type information from 1999 to 2023 were assessed from a recent tillage dataset generated based on time-series Landsat observations and a transfer learning framework STaPL (Scale Transfer with Pseudo-Labeling) (25). STaPL classifies tillage types without using ground tillage records for training. Instead, fields are sampled in each county and pseudo-labels (low till or high till) are assigned to each sampled fields proportionally to USDA county-level tillage statistics. After quality control, monthly vegetation and tillage indices and elevation for each field and the corresponding pseudo labels are used to train a random forests (RF) classifier for tillage type mapping. Comparison of STaPL predictions with an independent ground-based tillage dataset that spans eight years and more than 25,000 field-level observations showed that STaPL has a strong temporal generalizability and achieved an overall accuracy of 75% and a F1 score of 80% for low-till class, outperforming the models trained using the ground-based tillage records. When aggregated to the county and state levels, STaPL tillage maps exhibit strong agreement with official tillage statistics at both the county ($r^2 = 0.65$) and state level ($r^2 = 0.83$).

Annual yield data for corn and soybean from 1999 to 2023, with a spatial resolution of 30 meters, were sourced from the QDANN-derived yield maps (39). QDANN (Quantile loss Domain Adversarial Neural Networks) is a transfer learning model that is trained to associate crop yield with crop greenness as measured by Landsat imagery, based on both a labeled county-level dataset and an unlabeled subfield-level dataset. When aggregated QDANN yield maps to the county level and compared to USDA yield records, the product attains an R^2 of 84% for corn and 80% for soybean.

The USDA Crop Sequence Boundaries (CSB) dataset from USDA's Economic Research Service was used to locate fields and measure the field-level yields and tillage types (40). The CSB identifies regions with consistent cropping patterns by integrating historical cropland data layer (CDL) (41) with transportation networks and encompasses areas with similar cropping sequences. Finally, irrigated fields were identified using Landsat-based Irrigation Dataset (LANID) (42) and removed from the dataset.

Preprocessing of time-series field records

We reconstructed field-level tillage histories from annual time-series records by sorting observations chronologically within each field. After removing duplicate observations and resolving missing or inconsistent entries, we applied temporal consistency checks to filter implausible one-year switches that were likely to reflect classification noise rather than true management change. We then identified each field's most recent transition into low-intensity tillage and computed, for every field-year, the number of consecutive years under low till since that transition. This duration measure was calculated up to the first observed reversion to high-intensity tillage, after which subsequent field-year records were excluded from the analysis. We imposed this restriction to ensure that the high-till comparison group consisted of field-years that had not previously adopted low till, thereby avoiding potential carryover effects of prior low-till management on subsequent yields.

Some fields were classified as low till during the first two years of the study period, accounting for less than 2% of the dataset. We excluded these fields because they may have adopted low-till practices before observations began in 1999-2000, which would bias our estimate of duration too low, and thereby inflate our resulting estimates of yield benefits per year of adoption. Sensitivity

analyses indicate that estimates based on the full sample of fields are slightly larger but remain broadly consistent with the main results (Fig S2).

Weather data

Weather data in 1999 to 2023 were collected from PRISM daily spatial climate dataset (43) and projected climate data under the high-emission scenario (SSP5-8.5) were drawn from the NEX-GDDP-CMIP6 dataset (44). The accumulative precipitation (PPT), the average growing degree days (GDD), and the average extreme degree days (EDD) during the planting (April to May) and growing seasons (June to September) were calculated and aggregated to the county level in each year. PPT quantifies the moisture that is essential for photosynthesis, nutrient absorption, and transpiration. GDD and EDD are commonly used to measure heat exposure of crops to moderate and extreme heat, respectively:

$$\text{GDD} = \sum_{h=1}^N (\max(0, \min(T_h - T_{min}, T_{max} - T_{min}))) \quad (1)$$

$$\text{EDD} = \sum_{h=1}^N (\max(0, T_h - T_{max}))) \quad (2)$$

where T_h is hourly temperature (in °C) and the sum is taken for each hour during the key growing season (Apr 1st- Sep 30th for corn and soybean). T_{max} and T_{min} denote the biological upper and lower temperature limits, beyond which crop development ceases to respond to temperature. T_{max} is 30 °C and T_{min} is 8 °C for corn and soybean. Hourly temperatures were derived using sinusoidal interpolation between the daily minimum and maximum temperatures.

Methods

Two-way fixed-effects (TWFE) analysis

We considered the outcome, y , as a function of treatment covariates (X), control covariates (D_i), and unobserved covariates (Z) at field i :

$$y_i = \beta X_i + \alpha D_i + \gamma Z_i + \epsilon_i \quad (3)$$

The potential for Z to be correlated with X can cause bias when estimating coefficients β . To control for unobserved spatial and temporal heterogeneity, we built panel regression models and introduced two-way fixed effects at each field i and year t :

$$y_{i,t} = \beta X_{i,t} + \alpha D_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,j} \quad (4)$$

The specification includes field fixed effects γ_i to absorb all time-invariant characteristics of each field i , such as underlying soil characteristics and topography. It also includes year fixed effects λ_t to control for shocks in a given year, such as weather or market conditions. The treatment covariates X are the low-till durations in the linear models and the low-till categories in duration-category models.

We used field and year fixed effects in the main analysis, estimating low-till effects after accounting for field-level time-invariant differences and Corn Belt-wide annual shocks. We further tested a more conservative specification with field and state $\times$ year fixed effects, where the state $\times$ year fixed effects control for state-level shocks in each year. For corn, the estimated yield effect was very similar to the main analysis, at 0.21% yr⁻¹ compared to 0.20 % yr⁻¹. For soybean, the estimated yield effects attenuated to 0.11% yr⁻¹ compared to 0.16 % yr⁻¹ in the main analysis. The attenuation suggests that state-year variation contributes to the soybean yield effects estimated in the main analysis. One possible explanation is that soybean yield responses are more sensitive to weather conditions, as indicated by the weather-binned models, and this greater sensitivity may reinforce cross-state gradients. When state $\times$ year fixed effects are included, these cross-state annual gradients are absorbed, leaving identification from within-state-year comparison.

We further conducted leave-one-state-out validation, in which all fields from a single state were excluded before fitting the linear models with field and year fixed effects. The estimated coefficients were consistent across all models, with each showing that longer low-till durations were associated with progressively greater yield benefits (Fig S5). As a robustness check, these results demonstrate the estimated effects of low-till duration are stable across the study area and are not driven by any particular region.

Sun-Abraham (SA) interaction-weighted estimator

Our main specification is a TWFE regression of log yield on low-till duration with field and year fixed effects. When treatment timing is staggered and effects evolve with exposure, the TWFE coefficient is a weighted sum of underlying treatment effects in which some weights may be negative, because already-treated units serve as controls for later-treated ones (27). In our case, after residualizing duration on the fixed effects and weather controls and computing the implicit weights on treated field-years, 38.7% treated corn samples and 36.3% treated soybean samples receive negative weight, accounting for 13.6% and 12.8% of total absolute weight, respectively. We therefore treat the TWFE estimates as requiring corroboration.

As that corroboration, we implement the Sun-Abraham (SA) interaction-weighted estimator. Fields are assigned to adoption cohorts by the calendar year G_i in which their first continuous low-

till spell begins, binned into five cohorts (2000-2004, 2005-2009, 2010-2014, 2015-2019, 2020-2023). Event time k , defined as the number of years since G_i , is binned as ≤ -11 , $-10:-8$, $-7:-5$, $-4:-3$, -2 , -1 , 0 , $1:3$, $4:8$, $9:13$, $14:18$, ≥ 19 , where $k = 0$ is the first low-till year. We estimated the following cohort-specific event-study specification:

$$y_{i,t} = \sum_g \sum_{k \geq 0} \delta_{gk} \mathbf{1}(G_i = g) \mathbf{1}(t - g = k) + \alpha D_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,j} \quad (5)$$

in which δ_{gk} represents the low-till treatment effect for fields first adopting low till in year g at event time k . The years before adoption, $k < 0$, was omitted as the reference period. Identification comes from comparing treated fields with fields that had not yet adopted low-till management in the same calendar year. The interaction-weighted estimate for each event time k is then obtained by aggregating cohort-specific estimates:

$$\beta_k^{SA} = \sum_g \omega_{gk} \delta_{gk} \quad (6)$$

where ω_{gk} is the share of observations at event time k contributed by cohort g , with

$$\omega_{gk} = \frac{N_{gk}}{\sum_g N_{gk}} \quad (7)$$

Here, N_{gk} is the number of field-year observations from cohort g observed at event time k . The resulting β_k^{SA} estimates describe how low-till yield effects evolve since adoption while avoiding the negative-weighting problem that can arise in TWFE models. In our analysis, this SA estimator provides a robustness check on whether the observed yield response reflect sustained effects of low-till adoption rather than artifacts of staggered adoption timing. In addition to using $k < 0$ as the reference period (Fig S6), we also tested using $k = -4$: -1 (the fourth to the first year before adoption) as the reference periods, and both agreed well with TWFE estimates (Fig S7). We retain TWFE as our preferred approach primarily because it can examine effects of adoption duration regardless of whether we consider only continuous adopters or include fields that revert to conventional tillage in some years (roughly half our sample), whereas SA only considers effects of duration since the initial adoption of a binary treatment (i.e. continuous adopters in our context).

Weather-binned estimator

This analysis is motivated by the possibility that average treatment effects may mask important heterogeneity across weather regimes. We built weather-binned estimators which allow the relationship between weather exposure and yield to be flexible and nonlinear (45).

When building the weather-binned estimator, each of the five weather variables was used as the focal weather variable $D'_{i,t}$ and we binned observations on $D'_{i,t}$. The remaining weather variables were included additively as controls outside the bins, which helps isolate heterogeneity with respect to the focal weather dimension. For a given $D'_{i,t}$, we ordered observations by its value and assigned them to low, middle, and high bins according to the focal-weather distribution. This means that the bin thresholds differ across weather variables, and the same field-year observation may fall into different bins in different panels depending on the focal weather variable selected.

Again, we included field fixed effects γ_i in each weather-binned estimator to control for time-invariant differences across fields and year fixed effects λ_t to capture shocks common to all fields in a given year. Standard errors were clustered at the county level to account for spatial correlation in unobserved shocks. Specifically,

$$y_i = \sum_{b=1}^3 \left(\mu_b + \beta_b X_{i,t} + \alpha_b (C_{i,t} - c_b) + \delta_b X_{i,t} (C_{i,t} - c_b) \right) \mathbf{1}_b + \alpha Z_{i,t} + \gamma_i + \lambda_t + \epsilon_{i,j} \quad (5)$$

in which $X_{i,t}$ is the treatment for field i in year t ; $C_{i,t}$ is the focal weather variable and $Z_{i,t}$ is the remaining weather covariate; b is the bin number; $\mathbf{1}_b$ is a binary indicator, and it is 1 if $D_{i,t}$ falls in bin b ; μ_b is the control-group intercept; β_b and α_b are the estimated coefficients for the treatment and the weather covariate; δ_b is the estimated coefficient for their interaction term; c_b is the median value of the focal weather variable in each weather bin. We centered weather covariates at the median value of each bin, so that coefficients are interpreted relative to the median of each weather interval.

The main analysis groups weather variables into bottom-quartile, middle-half, and top-quartile bins. This 25-50-25 split emphasizes lower- and upper-tail weather conditions while retaining adequate sample size for estimation. To assess sensitivity to this choice, we also estimate an alternative specification using equal tercile bins. The estimated effects are similar across the two specifications (Fig S4), indicating that the conclusions are robust to reasonable alternative definitions of weather bins.

Scenario analysis

We conducted two scenario analyses: In the first historical counterfactual analysis, we assumed a 2012-like heatwave happened in the study area. The average weather condition in 2010s (2010 to 2019) based on the PRISM dataset was used as the baseline. In the second future climate-change scenario, we calculated the projected average weather conditions in 2030s (2030 to 2039) based on the NEX-GDDP-CMIP6 dataset under the high-emission scenario (SSP5-8.5). Meanwhile, the average weather condition in 2000s (2000 to 2009) based on the PRISM dataset was used as the baseline.

To account for uncertainty associated with individual climate models, we used an ensemble of climate model projections to simulate future climate scenarios. Specifically, we obtained projected future precipitation, GDD, and EDD from 30 climate models in the NEX-GDDP-CMIP6 dataset. For each model, weather variables were aggregated to the county level, after which the median across all models was calculated for each year. Finally, county-level averages over the period 2030–2039 were computed to represent the projected average weather conditions in the 2030s. Meanwhile, historical simulations from the same ensemble of climate models were used to represent climate conditions during the 2000s. For each weather variable, the difference between the projected conditions in the 2030s and the historical simulations in the 2000s were calculated to quantify the projected climate change. These climate deltas were then added to the observed average weather during the 2000s from the PRISM dataset to derive the weather conditions in the 2030s. Rather than using the raw climate model projections directly, we adopted the delta-based approach to reduce the influence of systematic biases in the climate model simulations.

In both scenario analysis, the EDD-binned estimator was used to estimate the model-fitted yields for each field under alternative low-till adoption and duration scenarios. We adopted the EDD-binned estimator because extreme heat is a major threat to crop yields, and EDD showed the largest changes across the scenarios. We assumed a constant year fixed effect, using the estimated year fixed effects for 2012 and 2005 in the first and second analyses, respectively. This assumption removes long-term yield trends, allowing the estimated yield changes to reflect only the effects of climate conditions and differences in low-till adoption durations. Finally, the area-weighted average yields were reported.

Supplemental Tables

Table S1. Summary of coefficients from the linear model for continued low-till adoption on log-transformed corn yields estimated using a two-way fixed-effects panel regression (field and year fixed effects). Coefficients are also expressed as percentage effects (pct) on yield, with corresponding 95% confidence intervals (CI). Standard errors are clustered by county and observations are weighted by field area. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Term	Estimate	Std. Error	Pct effect	Pct effect CI
Low-till duration	0.001984***	0.000269	0.1986%	[0.1457%, 0.2514%]
GDD, Apr-May	0.000258***	0.000043	0.0258%	[0.0174%, 0.0343%]
PPT, Apr-May	-0.000203***	0.000014	-0.0203%	[-0.0230%, -0.0175%]
GDD, Jun-Sep	0.000094**	0.000036	0.0094%	[0.0023%, 0.0165%]
PPT, Jun-Sep	-0.000004	0.000011	-0.0004%	[-0.0026%, 0.0018%]
EDD, Jun-Sep	-0.009307***	0.000232	-0.9263%	[-0.9713%, -0.8813%]
Observations	22,970,456			
Adjusted R2	0.688001			
Within R2	0.185881			

Table S2. Summary of coefficients from the linear model for continued low-till adoption on log-transformed soybean yields estimated using a two-way fixed-effects panel regression (field and year fixed effects). Coefficients are also expressed as percentage effects (pct) on yield, with corresponding 95% confidence intervals (CI). Standard errors are clustered by county and observations are weighted by field area. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Term	Estimate	Std. Error	Pct effect	Pct effect CI
Low-till duration	0.001591***	0.000218	0.1592%	[0.1163%, 0.2021%]
GDD, Apr-May	0.000578***	0.000036	0.0578%	[0.0508%, 0.0648%]
PPT, Apr-May	-0.000121***	0.000014	-0.0121%	[-0.0149%, -0.0092%]
GDD, Jun-Sep	-0.000004	0.000028	-0.0004%	[-0.0058%, 0.0051%]
PPT, Jun-Sep	0.000078***	0.000010	0.0078%	[0.0058%, 0.0098%]
EDD, Jun-Sep	-0.005933***	0.000145	-0.5916%	[-0.6198%, -0.5633%]
Observations	20,753,599			
Adjusted R2	0.682357			
Within R2	0.135053			

Table S3. Summary of coefficients on different durations of low-till adoption on the logarithm of crop yields in the panel regression model using two-way fixed effects (field and year). The reference category is high-till field-years with no prior low-till adoption. Standard errors are clustered by county and observations are weighted by field area. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Term	Corn Estimate	Std. Error	Soybean Estimate	Std. Error
1-4 years	0.009245***	0.001575	0.004034**	0.001425
5-9 years	0.019810***	0.002460	0.011061***	0.001891
10-14 years	0.030166***	0.003342	0.017384***	0.002536
15-19 years	0.033745***	0.004142	0.025176***	0.003475
20+ years	0.041075***	0.005024	0.031440***	0.004370
GDD, Apr-May	0.000251***	0.000044	0.000578***	0.000036
PPT, Apr-May	-0.000203***	0.000014	-0.000121***	0.000015
GDD, Jun-Sep	0.000093*	0.000036	-0.000004	0.000028
PPT, Jun-Sep	-0.000004	0.000011	0.000078***	0.000010
EDD, Jun-Sep	-0.009319***	0.000232	-0.005934***	0.000145
Observations	22,970,456		20,753,599	
Adjusted R2	0.688128		0.682328	
Within R2	0.186213		0.134975	

Table S4. Summary of coefficients from the linear model for cumulative low-till adoption on log-transformed corn yields estimated using a two-way fixed-effects panel regression (field and year fixed effects). The treatment is the cumulative number of low-till years and the sample retains fields that reverted to conventional tillage. Coefficients are also expressed as percentage effects (pct) on yield, with corresponding 95% confidence intervals (CI). Standard errors are clustered by county and observations are weighted by field area. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Term	Estimate	Std. Error	Pct effect	Pct effect CI
Cumulative low-till years	0.001795***	0.000265	0.1796%	[0.1275%, 0.2318%]
GDD, Apr-May	0.000376***	0.000034	0.0376%	[0.0310%, 0.0441%]
PPT, Apr-May	-0.000192***	0.000012	-0.0192%	[-0.0216%, -0.0169%]
GDD, Jun-Sep	0.000101**	0.000032	0.0101%	[0.0039%, 0.0163%]
PPT, Jun-Sep	-0.000051***	0.000010	-0.0051%	[-0.0070%, -0.0033%]
EDD, Jun-Sep	-0.009270***	0.000206	-0.9227%	[-0.9627%, -0.8827%]
Observations	44,456,757			
Adjusted R2	0.708376			
Within R2	0.189187			

Table S5. Summary of coefficients from the linear model for cumulative low-till adoption on log-transformed soybean yields estimated using a two-way fixed-effects panel regression (field and year fixed effects). The treatment is the cumulative number of low-till years and the sample retains fields that reverted to conventional tillage. Coefficients are also expressed as percentage effects (pct) on yield, with corresponding 95% confidence intervals (CI). Standard errors are clustered by county and observations are weighted by field area. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Term	Estimate	Std. Error	Pct effect	Pct effect CI
Cumulative low-till years	0.001554***	0.000213	0.1555%	[0.1136%, 0.1973%]
GDD, Apr-May	0.000560***	0.000030	0.0561%	[0.0502%, 0.0620%]
PPT, Apr-May	-0.000134***	0.000012	-0.0134%	[-0.0157%, -0.0111%]
GDD, Jun-Sep	0.000016	0.000025	0.0016%	[-0.0032%, 0.0065%]
PPT, Jun-Sep	0.000050***	0.000009	0.0050%	[0.0031%, 0.0068%]
EDD, Jun-Sep	-0.005299***	0.000142	-0.5285%	[-0.5562%, -0.5008%]
Observations	40,299,697			
Adjusted R2	0.708876			
Within R2	0.113379			

Table S6. Summary of coefficients on different cumulative durations of low-till adoption on the logarithm of crop yields in the panel regression model using two-way fixed effects (field and year). The reference category is field-years with no prior low-till adoption. Standard errors are clustered by county and observations are weighted by field area. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Term	Corn		Soybean	
	Estimate	Std. Error	Estimate	Std. Error
1-4 years	0.002491*	0.001110	0.002813**	0.000992
5-9 years	0.010356***	0.001906	0.009473***	0.001511
10-14 years	0.018144***	0.002687	0.015272***	0.002167
15-19 years	0.023124***	0.003473	0.021851***	0.002949
20+ years	0.032685***	0.004423	0.029852***	0.003729
GDD, Apr-May	0.000375***	0.000034	0.000560***	0.000030
PPT, Apr-May	-0.000193***	0.000012	-0.000134***	0.000012
GDD, Jun-Sep	0.000100**	0.000031	0.000016	0.000025
PPT, Jun-Sep	-0.000052***	0.000009	0.000050***	0.000009
EDD, Jun-Sep	-0.009277***	0.000206	-0.005305***	0.000143
Observations	44,456,757		40,299,697	
Adjusted R2	0.708320		0.708818	
Within R2	0.189032		0.113201	

Table S7. Summary of weather-binned estimates of the effect of low-till duration on log-transformed corn yields in the panel regression model using two-way fixed effects (field and year). For each focal weather variable, observations are assigned to low (bottom quartile), middle (middle half) and high (top quartile) bins, and the remaining weather variables enter additively as controls. Coefficients give the effect per additional year of continuous low till, evaluated at the median of each bin. GDD and EDD are in degree days (°C-days) and PPT is in millimetres (mm). Bin sample sizes are 5.85, 11.70 and 5.85 million observations for the low, middle and high bins respectively. Standard errors are clustered by county and observations are weighted by field area. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Weather	Bin	Bin range	Estimate	Std. Error	Pct effect	Pct effect CI
GDD, Apr-May	Low	[76, 282]	0.002569***	0.000445	0.257%	[0.170%, 0.345%]
	Mid	[282, 407]	0.001635***	0.000293	0.164%	[0.106%, 0.221%]
	High	[407, 728]	0.002092***	0.000314	0.209%	[0.148%, 0.271%]
PPT, Apr-May	Low	[25, 146]	0.002163***	0.000330	0.216%	[0.152%, 0.281%]
	Mid	[146, 232]	0.001738***	0.000292	0.174%	[0.117%, 0.231%]
	High	[232, 655]	0.001227***	0.000344	0.123%	[0.055%, 0.190%]
GDD, Jun-Sep	Low	[884, 1,392]	0.003003***	0.000497	0.301%	[0.203%, 0.399%]
	Mid	[1,392, 1,620]	0.001674***	0.000323	0.168%	[0.104%, 0.231%]
	High	[1,620, 2,136]	0.002203***	0.000307	0.221%	[0.160%, 0.281%]
PPT, Jun-Sep	Low	[88, 301]	0.003146***	0.000293	0.315%	[0.257%, 0.373%]
	Mid	[301, 445]	0.001960***	0.000283	0.196%	[0.141%, 0.252%]
	High	[445, 1,048]	0.001240***	0.000316	0.124%	[0.062%, 0.186%]
EDD, Jun-Sep	Low	[0, 5]	0.002299***	0.000443	0.230%	[0.143%, 0.317%]
	Mid	[5, 19]	0.001052***	0.000308	0.105%	[0.045%, 0.166%]
	High	[19, 135]	0.002960***	0.000305	0.296%	[0.237%, 0.356%]

Table S8. Summary of weather-binned estimates of the effect of low-till duration on log-transformed soybean yields in the panel regression model using two-way fixed effects (field and year). For each focal weather variable, observations are assigned to low (bottom quartile), middle (middle half) and high (top quartile) bins, and the remaining weather variables enter additively as controls. Coefficients give the effect per additional year of continuous low till, evaluated at the median of each bin. GDD and EDD are in degree days (°C-days) and PPT is in millimetres (mm). Bin sample sizes are 5.29, 10.58 and 5.29 million observations for the low, middle and high bins respectively. Standard errors are clustered by county and observations are weighted by field area. *** $p < 0.001$, ** $p < 0.01$, * $p < 0.05$.

Weather	Bin	Bin range	Estimate	Std. Error	Pct effect	Pct effect CI
GDD, Apr-May	Low	[83, 291]	0.001207***	0.000316	0.121%	[0.059%, 0.183%]
	Mid	[291, 421]	0.000398	0.000218	0.040%	[-0.003%, 0.082%]
	High	[421, 728]	0.003051***	0.000249	0.306%	[0.257%, 0.354%]
PPT, Apr-May	Low	[25, 150]	0.001736***	0.000280	0.174%	[0.119%, 0.229%]
	Mid	[150, 240]	0.001404***	0.000237	0.140%	[0.094%, 0.187%]
	High	[240, 655]	0.001139***	0.000284	0.114%	[0.058%, 0.170%]
GDD, Jun-Sep	Low	[884, 1,409]	-0.000192	0.000400	-0.019%	[-0.098%, 0.059%]
	Mid	[1,409, 1,664]	0.000228	0.000206	0.023%	[-0.018%, 0.063%]
	High	[1,664, 2,136]	0.003567***	0.000268	0.357%	[0.305%, 0.410%]
PPT, Jun-Sep	Low	[88, 299]	0.002375***	0.000292	0.238%	[0.180%, 0.295%]
	Mid	[299, 442]	0.001672***	0.000219	0.167%	[0.124%, 0.210%]
	High	[442, 1,048]	0.000708**	0.000269	0.071%	[0.018%, 0.124%]
EDD, Jun-Sep	Low	[0, 5]	0.000543	0.000298	0.054%	[-0.004%, 0.113%]
	Mid	[5, 21]	0.000692**	0.000223	0.069%	[0.026%, 0.113%]
	High	[21, 135]	0.003641***	0.000269	0.365%	[0.312%, 0.418%]

Table S9. The observed weather conditions in 2005s, 2010s, 2012, and projected weather in 2035.

Period	GDD, Apr-May (°C-days)	PPT, Apr-May (mm)	GDD, Jun-Sep (°C-days)	PPT, Jun-Sep (mm)	EDD, Jun-Sep (°C-days)
2000s	357.338	180.909	1517.479	357.217	23.145
2010s	364.193	208.42	1561.656	393.512	24.463
2012	433.337	152.154	1591.718	234.616	56.458
2035s	420.035	194.153	1674.099	354.58	51.098

Supplemental Figures

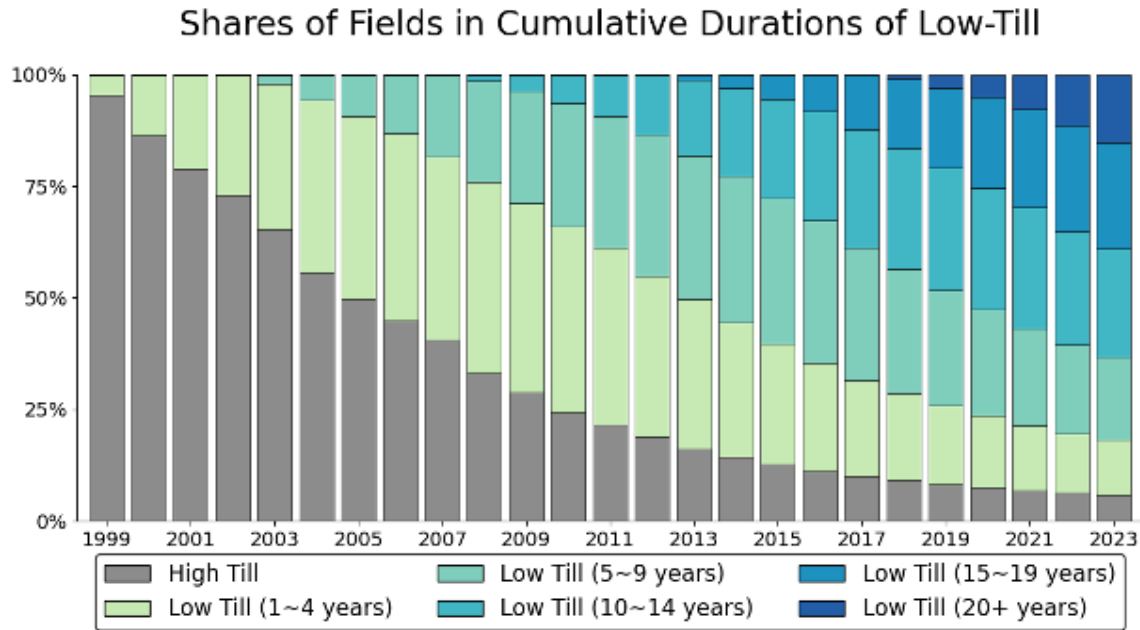


Fig. S1. Shares of fields with cumulative low-till adoption for different durations, illustrating the growing share of long-term adopters. The durations for continuous low-till adoption show a similar pattern (Fig. 1(c)).

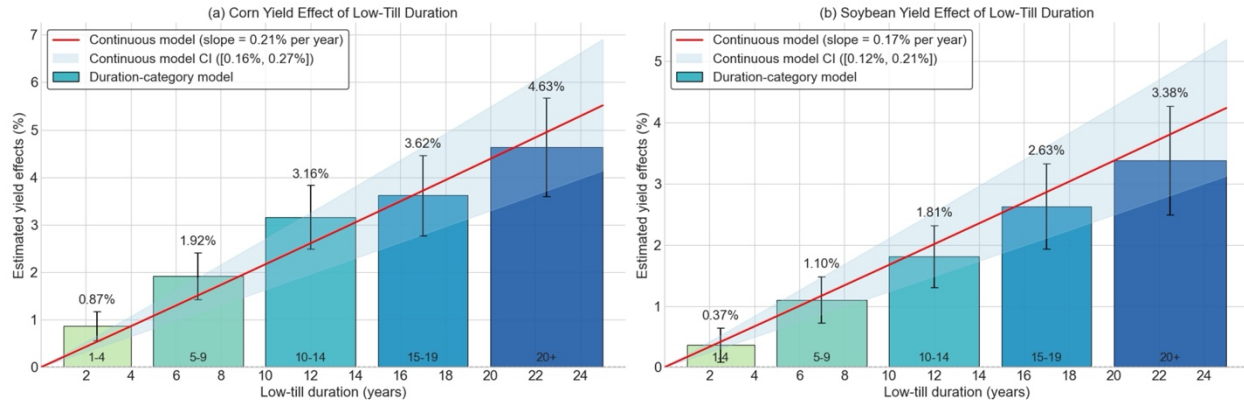


Fig. S2. Effects of low-till duration models are robust to the inclusion of pre-1999 adopters. Low-till duration models are fitted using all fields, including fields flagged as low till in the first two years of the study record. All models include field and year fixed effects, are weighted by field area, and have standard errors clustered by county. Error bars denote 95% confidence intervals. The estimated yield effects are slightly larger than those in the main analysis (Fig. 3), likely because fields flagged as low till in 1999 or 2000 had adopted it before the study period and therefore had already accumulated greater benefits.

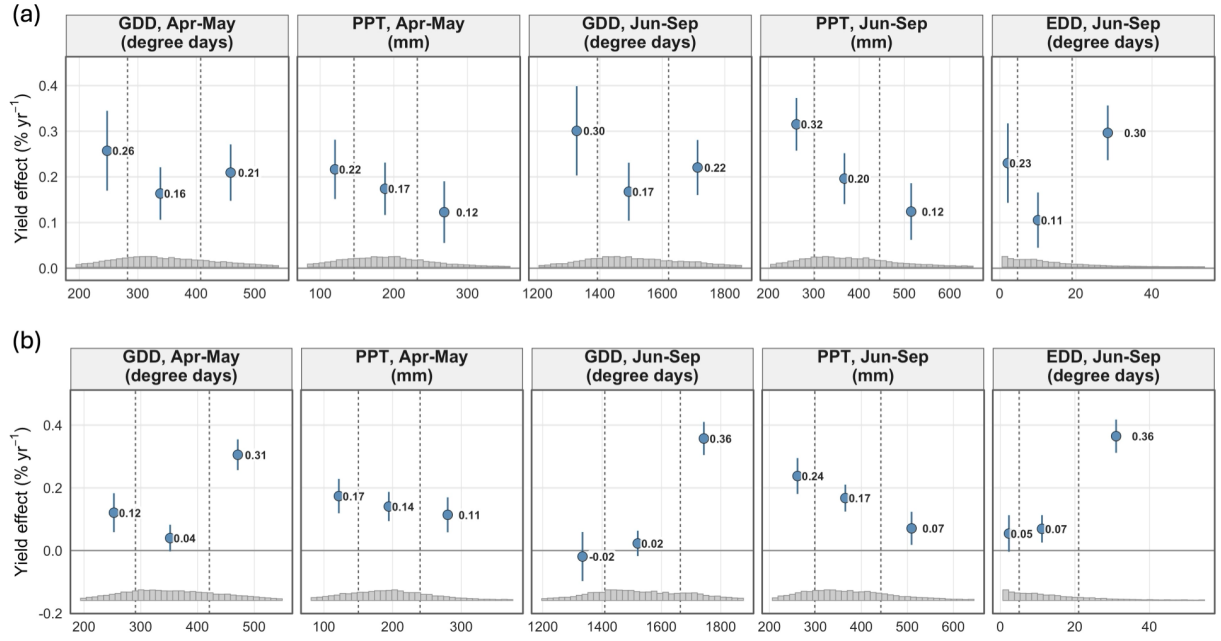


Fig. S3. **Effects of low-till adoption on yields vary across weather bins.** Estimated effect of the one additional year of continuous low-till adoption on (a) corn and (b) soybean yields. For each focal weather variable, observations are assigned to low (bottom quartile), middle (middle half) and high (top quartile) bins, and the remaining weather variables enter additively as controls. In each panel, the focal weather variable defined the bins, and the remaining four weather variables enter additively as linear controls; bin-specific coefficients are evaluated at the median of each bin and plotted at that value. All models include field and year fixed effects, are weighted by field area, and have standard errors clustered by county. Error bars denote 95% confidence intervals, and histograms along the horizontal axis show the distribution of each weather covariate (middle 90% shown).

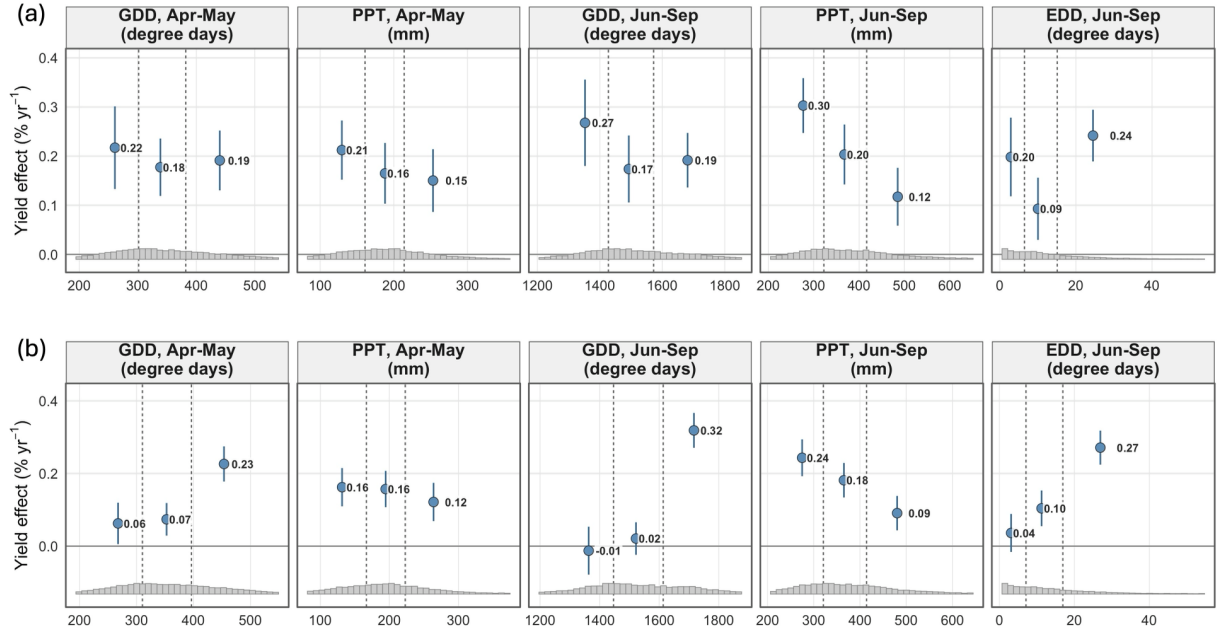


Fig. S4. **Weather-binned estimates are robust to the definition of the weather bins.** Estimated effect of the one additional year of continuous low-till adoption on (a) corn and (b) soybean yields, from an alternative specification in which each focal weather variable is divided into terciles rather than the 25-50-25 split used in the main analysis (Fig 4 and Fig S3). In each panel, the focal weather variable defined the bins, and the remaining four weather variables enter additively as linear controls; bin-specific coefficients are evaluated at the median of each bin and plotted at that value. All models include field and year fixed effects, are weighted by field area, and have standard errors clustered by county. Error bars denote 95% confidence intervals, and histograms along the horizontal axis show the distribution of each weather covariate (middle 90% shown).

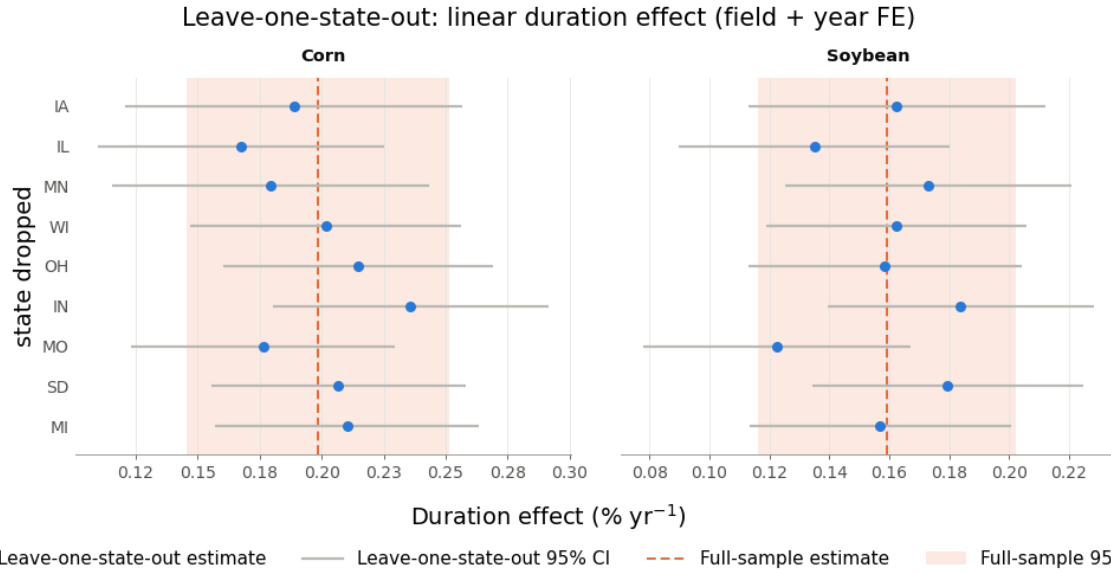


Fig. S5. **Leave-one-state-out estimates of the linear low-till duration effect.** For each crop and excluded state, each point shows the estimated percent yield effect of one additional low-till year when the state is omitted from the sample. Horizontal bars show the 95% confidence interval. The dashed vertical line shows the full-sample estimate, and the shaded band shows its 95% confidence interval.

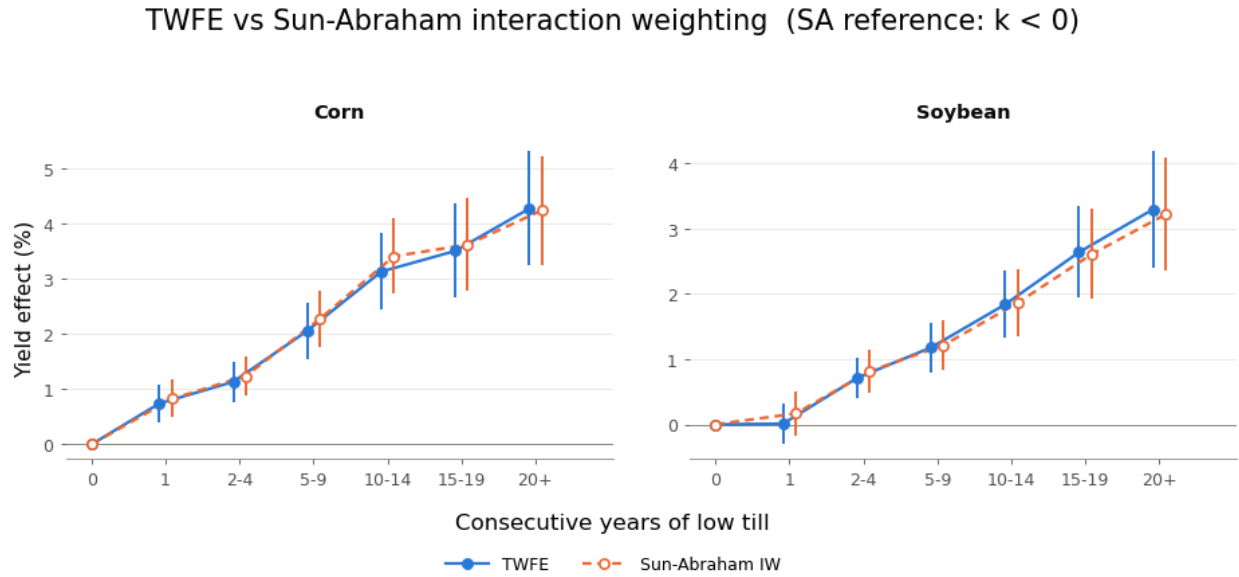


Fig. S6. TWFE and Sun-Abraham interaction-weighted estimates by consecutive years of low till adoption. Points show estimated yield effects for each low-till duration bin for corn and soybean. The blue solid series reports two-way fixed effects estimates, and the orange dashed series reports Sun-Abraham interaction-weighted estimates. Vertical bars show 95% confidence intervals. The omitted reference category for the Sun-Abraham specification is the pre-treatment period, $k < 0$. Effects are expressed as percent yield changes relative to the control baseline.

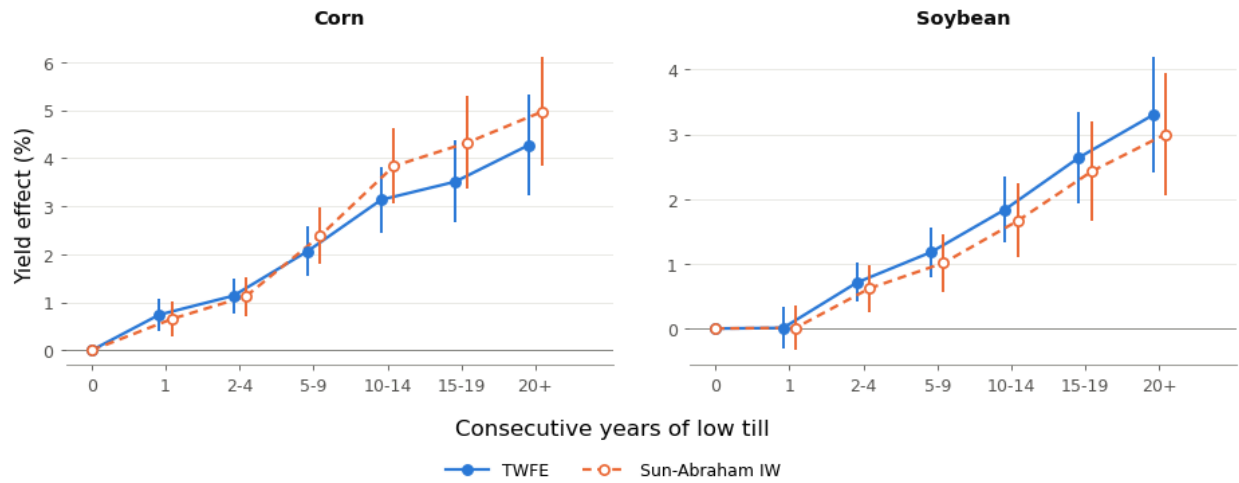
TWFE vs Sun-Abraham interaction weighting (SA reference: $k = -4:-1$)

Fig. S7. **TWFE and Sun-Abraham interaction-weighted estimates by consecutive years of low till adoption.** Points show estimated yield effects for each low-till duration bin for corn and soybean. The blue solid series reports two-way fixed effects estimates, and the orange dashed series reports Sun-Abraham interaction-weighted estimates. Vertical bars show 95% confidence intervals. The omitted reference category for the Sun-Abraham specification is the pre-treatment period, $k = -4:-1$. Effects are expressed as percent yield changes relative to the control baseline.

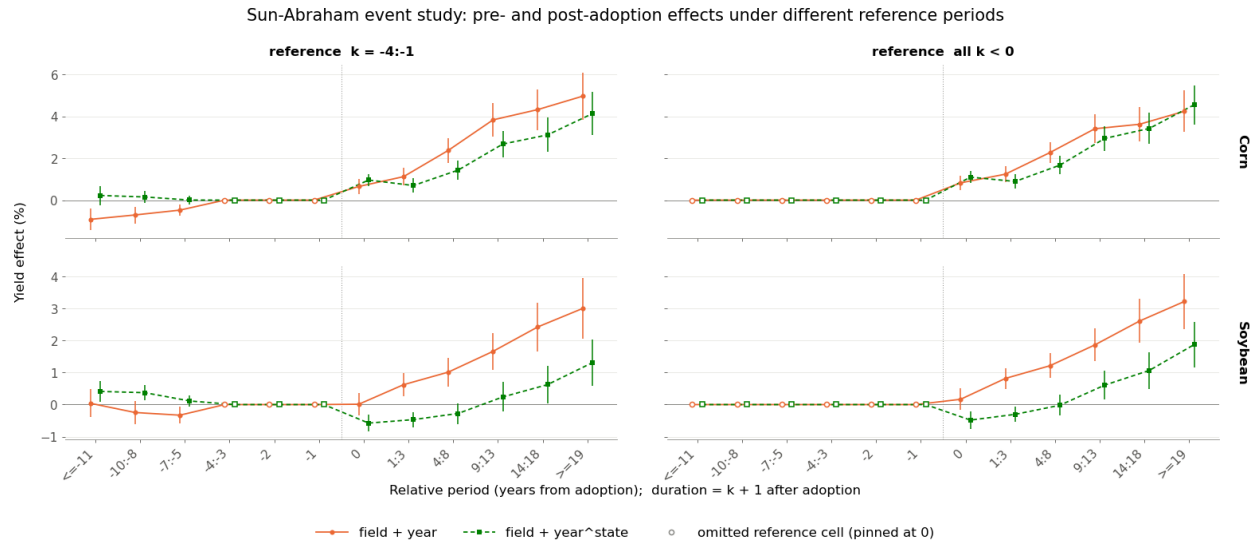


Fig. S8. Sun-Abraham interaction-weighted estimates by consecutive years of low till adoption. Both pre- and post-adoption effects are estimated under two different reference periods ($k=-4:-1$ and $k<0$).