



# Large-scale farmer-led experiment demonstrates positive impact of cover crops on multiple soil health indicators

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**Cover crops are touted for their potential agronomic and environmental benefits, and are currently incentivized through state, federal and private investment in the USA. There is a need to quantify the impact of on-farm use of cover crops at spatial (2–5 years) and temporal (regional-to-national) scales aligned with such investment programmes. Here we report soil health data from a farmer-led trial of cover crops on 1,522 strip-years, from 78 farms across 9 US states over 5 years. We found that up to 5 years of cover crop use had small but increasing impacts on four of six selected soil health indicators, with active carbon concentration responding the most rapidly. Soil texture, the length of time a field was in the trial and a farm-level random effect were also strongly related to soil health properties. Our results fit with evidence from controlled trials and suggest that the use of cover crops can begin to influence soil health within several years after adoption.**

There is growing interest in the USA in incentivizing agriculture to provide public benefits, such as water quality, biodiversity and greenhouse gas reduction. Yet, adoption of practices that provide these benefits is low: cover crops were used on less than 10% of the country's cropland between 2007 and 2017<sup>1,2</sup>. Long-term research<sup>3</sup>, literature synthesis<sup>4,5</sup> and on-farm research<sup>6,7</sup> have shown benefits—and potential trade-offs—of cover crops. A gap in the literature exists concerning the impact of these practices on real farms, across large scales and at temporal scales that mirror incentive programmes.

Most on-farm studies researching cover crops prescribe how cover crops are implemented to ensure consistency of the treatment<sup>8–10</sup>. This approach has clear strengths, but often ignores the role of farmer preferences for management practices and implementation timelines, which could shape the impact of these practices on working farmland. In rangeland sciences, similar differences between how practices are studied by researchers and how they are implemented by farmers have created tensions and limited innovation in research and management<sup>11</sup>.

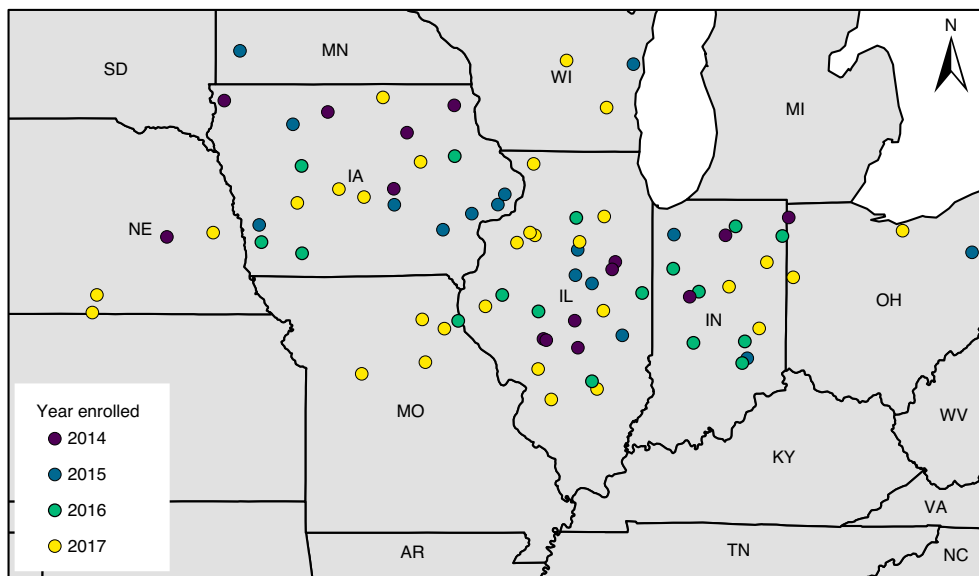
It is largely unknown whether participatory, on-farm research leads to different conclusions about the impact of cover crops when compared to more traditional research approaches. Differences could arise because farmers may be more likely to make secondary adjustments to management practices to avoid adverse outcomes. Differences could also occur because risk-averse farmers may be more likely to implement practices through a series of incremental changes—which may reduce the probability of an adverse impact but also result in a lag in soil property changes. Finally, most studies on real farms are conducted at local-to-state scales<sup>12</sup>; as changes in soil properties depend on soil type, management and climate, small-scale studies may have limited relevance for regional-to-national efforts. Meta-analyses that cover large scales often include studies from outside the USA<sup>13</sup>, which also limits their relevance for within-country prioritization. Evaluating the impact of cover crops in the context of participatory, on-farm research contributes to the critical question of whether cover crops

can deliver the suite of soil health benefits suggested by research trials. This knowledge is critical to inform efforts aimed at the adoption of cover crops and the ecosystem services generated through improved cropland management, particularly at a vital time in the development of public and private programmes that incentivize adoption and establish markets for ecosystem services<sup>14</sup>.

We report on 5 years of soil health data collected from a network of farmer-led experiments across 9 states in the USA (Fig. 1). Soil health is a holistic concept that integrates the biological, physical and chemical aspects of soil<sup>15</sup>, and several studies have analysed indicators of soil health<sup>16–18</sup>. Here we examine six physical and biological indicators from the Cornell Comprehensive Assessment of Soil Health (see Methods)—namely active carbon, aggregate stability, autoclaved-citrate extractable (ACE) soil protein, organic matter, respiration and available water capacity (Table 1). We expected that soil health properties would change more slowly in this farmer-led experiment than on research trials because of farmer risk management potentially leading to incremental changes in practices compared to research trials that implement fairly strong differences in practices rapidly, as well as other covarying factors not controlled for in a real-world farm. Following this expectation, we anticipated that we would not see changes in total organic matter and water retention, which are known to change over long periods and not respond to short-term cover crop use<sup>19</sup>. We expected that we may see changes in soil health properties for which there is evidence for short-term response to cover crops in the US Corn Belt. Studies have shown that cover crops can increase microbial biomass and particulate organic matter<sup>20</sup>, as well as water-stable aggregates<sup>19,21</sup>, in less than 5 years (farms in the dataset reported here had from 2 to 5 years of participation in a cover crop trial; see Methods).

Our data come from the Soil Health Partnership (SHP), a programme of the US-based National Corn Growers Association that supports farmers in conducting trials to compare conservation agriculture practices to typical management<sup>22</sup>. The programme includes more than 200 farmers in 16 states; the data we present are panel data from 78 farms in 9 states (Fig. 1). Each of these farms joined

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**Fig. 1 | Locations of SHP farms.** The points are coloured according to the year when the farm was enrolled in the programme.

**Table 1 | Summary statistics of soil properties by state for farms trialling cover cropping**

	IA (N = 399)	IL (N = 509)	IN (N = 280)	MO (N = 96)	NE (N = 88)	OH (N = 70)	WI (N = 56)
<b>Texture</b>							
Clay (%)	25 (± 4.7)	25 (± 5.0)	16 (± 5.7)	21 (± 4.3)	23 (± 4.6)	25 (± 3.9)	18 (± 11)
Silt (%)	59 (± 15)	69 (± 8.1)	44 (± 19)	64 (± 17)	69 (± 3.3)	47 (± 8.1)	43 (± 23)
Sand (%)	16 (± 17)	6.4 (± 6.4)	40 (± 23)	15 (± 21)	7.8 (± 3.0)	29 (± 11)	39 (± 30)
<b>Soil health</b>							
ACE soil protein (mg g soil <sup>-1</sup> )	5.5 (± 0.85)	5.0 (± 0.68)	4.8 (± 1.0)	4.5 (± 0.64)	5.3 (± 0.75)	4.1 (± 0.48)	4.4 (± 0.58)
Active carbon (ppm)	570 (± 120)	580 (± 130)	440 (± 120)	450 (± 120)	570 (± 100)	430 (± 95)	470 (± 160)
Aggregate stability (%)	25 (± 10)	22 (± 11)	21 (± 12)	17 (± 8.1)	16 (± 11)	16 (± 5.6)	25 (± 9.9)
Available water capacity (gH <sub>2</sub> O g soil <sup>-1</sup> )	0.27 (± 0.05)	0.29 (± 0.04)	0.21 (± 0.06)	0.27 (± 0.08)	0.33 (± 0.03)	0.23 (± 0.04)	0.21 (± 0.09)
Organic matter (%)	3.8 (± 0.99)	3.4 (± 0.92)	2.4 (± 0.46)	2.5 (± 0.40)	3.1 (± 0.46)	2.5 (± 0.52)	2.2 (± 0.98)
Respiration (mgCO <sub>2</sub> g soil <sup>-1</sup> )	0.50 (± 0.14)	0.42 (± 0.13)	0.43 (± 0.10)	0.47 (± 0.15)	0.45 (± 0.14)	0.45 (± 0.08)	0.44 (± 0.10)
<b>Years in trial</b>	1.5 (± 1.4)	2.1 (± 1.7)	1.6 (± 1.5)	1.3 (± 1.1)	2.2 (± 1.4)	2.0 (± 1.3)	1.9 (± 1.4)

The mean is reported with the standard deviation in parentheses. The sample size in the header refers to the number of strip-years per state. We removed data from the table for MN, which has fewer than three farms, to protect farmer anonymity per data use agreements. The data are grouped by state to demonstrate spatial variation in soil properties, and because states can represent important socioeconomic differences in cropping systems.

the SHP between 2014 and 2019 (farms were enrolled to the programme during these years), and implemented a replicated strip trial (typically 8 strips) on one field comparing cover-cropped strips to control strips with no cover crop.

## Results

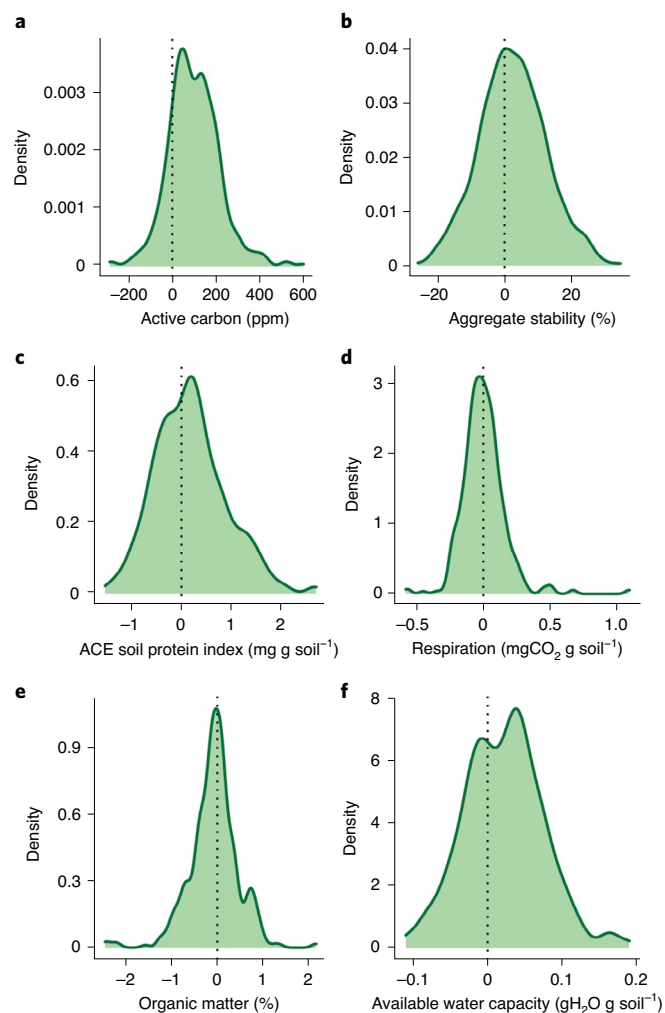
Four of six indicators of soil health, as measured by the Cornell Comprehensive Assessment of Soil Health, were found to be greater under cover crops compared to the control (Table 2, Fig. 2 and Supplementary Table 1). Active carbon (Supplementary

Table 2), aggregate stability (Supplementary Table 3), respiration (Supplementary Table 4) and total organic matter (Supplementary Tables 5 and 8) showed evidence of increase, while a soil protein index (Supplementary Table 6) and available water capacity (Supplementary Table 7) showed little evidence of change. Using statistical controls for time in the experiment, soil type and farm-level factors, we found that the effect increases over the course of the experiment (Fig. 3). Overall, the effect of cover crops is described by the coefficient on cover crop plus the coefficient on the interaction of cover crop and number of years of participation in the SHP.

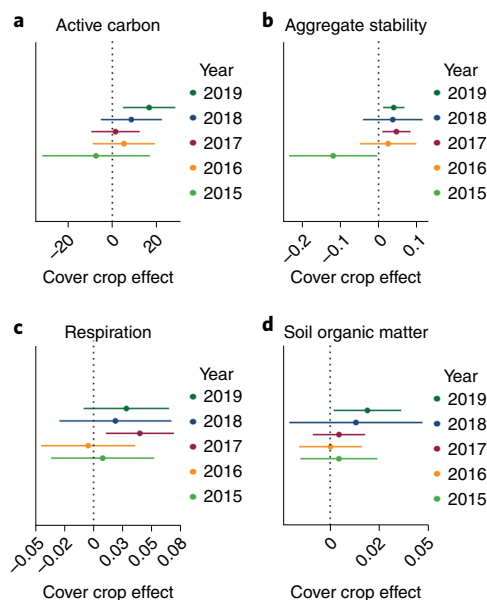
**Table 2 | Values of soil health properties for cover crop strips and control strips**

Soil health indicator	Units	Cover crop strip-years	Control strip-years
		(N = 549)	(N = 561)
ACE soil protein index	mg g soil <sup>-1</sup>	5.0 (± 0.87)	5.0 (± 0.92)
Active carbon	ppm	550 (± 130)	540 (± 130)
Aggregate stability	%	23 (± 11)	22 (± 11)
Organic matter	%	3.2 (± 0.98)	3.1 (± 0.98)
Respiration	mgCO <sub>2</sub> g soil <sup>-1</sup>	0.46 (± 0.14)	0.44 (± 0.14)
Available water capacity	gH <sub>2</sub> O g soil <sup>-1</sup>	0.27 (± 0.06)	0.27 (± 0.06)

For comparison purposes, the data in this table exclude values from baseline soil sampling. Mean values are shown with standard deviation in parentheses. The data are not controlled for other differences among farms and strips. Formal statistical comparisons are reported in Figs. 2 and 3 and Supplementary Tables 1–8.



**Fig. 2 | Distributions of cover-crop-related changes through time in soil health indicators. a**, Active carbon. **b**, Aggregate stability. **c**, ACE soil proteins. **d**, Cumulative CO<sub>2</sub> efflux (respiration) from 4-day incubations. **e**, Total soil organic matter by loss on ignition. **f**, Available water capacity. Changes show the difference in each soil health indicator for cover crop strips through time between the most recent soil sample and the baseline. Differences are not controlled for other properties that vary by strip and farm. Statistical effects are shown in Figs. 3 and 4.

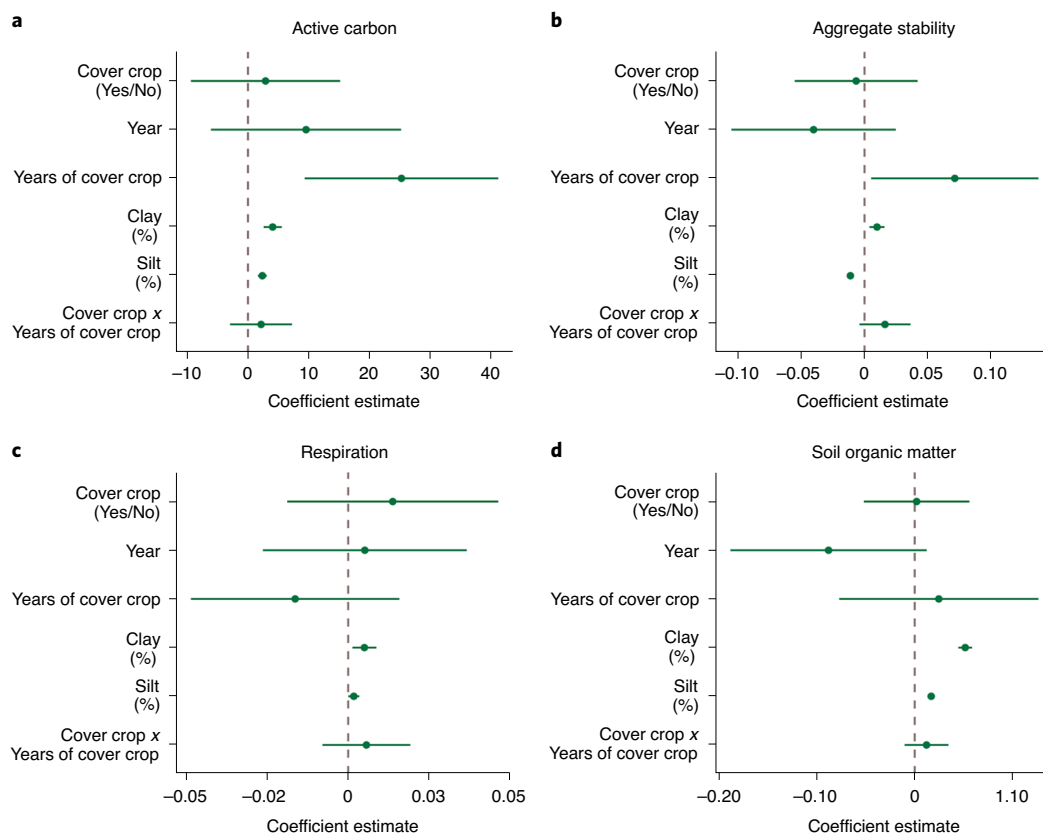


**Fig. 3 | Year-by-year coefficient plots of statistical models for soil health indicators that were found to change with up to 4 years of cover crops. a**, Active carbon. **b**, Aggregate stability. **c**, Cumulative CO<sub>2</sub> efflux (respiration) from 4-day incubations. **d**, Total soil organic matter by loss on ignition.

The statistical models are subset by year to show increasing effect through time. The points are mean values of coefficients and the bars are 95% confidence intervals of coefficient estimates. The different ranges in the x axis for the different panels are thus due to different ranges of the response variables. The magnitude of the difference in the coefficients between 2 years is the magnitude of the difference in the effect of those 2 years on the response variable.

The coefficient on the interaction alone describes how the rate of change differs between cover crop and control strips. Controlling for farm- and field-specific factors, active carbon increased 2.2 ppm more per year on cover crop strips than trial strips. Aggregate stability increased by 1.02 percentage points ( $e^{0.02}$ , see Supplementary Table 1) per year more on cover crop strips than control strips. Soil organic matter increased by 0.01% more per year on cover crop strips than on control strips.

We also found that the effect of soil texture—measured as the percentage of clay and the percentage of silt—was almost always a strong driver of soil health outcomes, although in some cases the directionality of the relationship varied (Fig. 4 and Supplementary Tables 1–8). As we included a farm-level random intercept in the model, the effect of texture represents the variation independent of farm-level variation—therefore, not representing the full effect of soil type. The soil organic matter model with a prior estimate (see Methods for explanation of priors) for clay had high overall accuracy (Supplementary Fig. 3), but estimated treatment effects about half as large as models without a prior. The fixed effects of the soil health models did not always explain large amounts of variance in the data. Only the models for active carbon (Supplementary Table 2), aggregate stability (Supplementary Table 3), soil organic matter (Supplementary Table 5) and available water capacity (Supplementary Table 7) had fixed effects explain more than 25% of the variation. All soil health indicators were strongly explained by farm-specific controls, evidenced by the high adjusted  $R^2$  values of the combined fixed and random effects (Supplementary Table 1). With farm-level intercepts, predictive ability was greater than 60% for all models except for respiration (42%, Supplementary Table 1).



**Fig. 4 | Regression coefficient plots for soil health indicators that were found to change with up to 4 years of cover crops. a,** Active carbon. **b,** Aggregate stability. **c,** Cumulative CO<sub>2</sub> efflux (respiration) from 4-day incubations. **d,** Total soil organic matter by loss on ignition. The soil organic matter model is estimated by maximum likelihood to be comparable with the other models shown. The points are mean values of coefficients and the bars are 95% confidence intervals of coefficient estimates.

## Discussion

On the basis of previous findings, we expected that active carbon, aggregate stability and respiration would increase with cover crop use over the timescale of this study. Our findings support this expectation. However, our observed changes in total organic matter by year differ from previous work finding that total carbon does not change at this approximate timescale of cover crop use<sup>19</sup>. In general, the mean changes in soil properties are still small relative to the range of the data; however, they may suggest a relevant trend given the steady increase in effect size over the course of the study period (Fig. 2). Hence, there needs to be more research highlighting how changes in soil health properties translate to agronomic and environmental outcomes, and what levels of change in these properties are necessary to confer such benefit. As soil health properties can be strongly related, some efforts have treated soil health as a latent variable that is then related to yield<sup>23</sup>.

We also found that the effect of soil texture on soil carbon was twice as large in the model without prior estimates for the relationship between clay and organic matter. Similarly, the cover crop-by-time effect was twice as large without a prior estimate, but had greater error. It was not clear which of these estimates is most accurate, but the discrepancy between the two highlights the potential for Bayesian analytical methods to provide different estimates of changes in soil carbon from frequentist statistical approaches when certain covariates are well established. More work, however, is needed in this area. It is important to note that we report only changes in soil carbon concentrations, not changes in stocks, because bulk density or mass-equivalent soil sampling is not part of the SHP sample protocol. There is great interest in, and controversy

over, how practices such as cover crops can impact soil carbon to contribute to climate mitigation<sup>24–27</sup>; however, our results cannot directly inform that debate.

The lack of change in available water capacity and the large amount of variation explained by farm-level controls suggest that this indicator is mediated by differences in soil type across farms, and may be less sensitive to management over the short term. This lower sensitivity to management may be because available water capacity is partially controlled by soil organic matter, and relatively large changes in soil organic matter would need to be achieved before observing changes in available water capacity. However, available water capacity probably underestimates the impact of soil carbon on water retention because greater carbon is also associated with greater water infiltration, not just water retention once infiltrated into the soil—and meta-analysis has shown that water infiltration is greater in the presence of soil health practices<sup>28,29</sup>. Furthermore, because laboratory measurement of available water capacity involves disturbances to soil physical structure through sieving, laboratory measurements of available water capacity do not necessarily reflect water retention dynamics in the field.

Most research on the impact of cover crops on soil health indicators has not been carried out in a participatory setting with farmers. This explains a large gap in the understanding of whether on-farm use of cover crops will have similar impacts to those found in cover crop trials. Our results have demonstrated that adoption of cover crops by farmers can result in measurable, field-level changes in soil health that are potentially greater than those suggested by research trials. Specifically, we found increases in soil organic matter by year where other studies have not over similar time frames. This,

in turn, highlights the need for longer-term research quantifying the impacts of conservation management systems in real-world settings, as well as connecting changes in soil health indicators to changes in agronomic and environmental outcomes, such as crop yield or water quality.

There are some important limitations to research on soil health indicators and aggregate indices. Some research suggests that aggregate indices of soil health may not be predictive of crop yield<sup>30</sup> (although individual indicators may be better predictors<sup>23,30</sup>). This could be related to a number of factors, including that an increase in a soil health indicator will impact yield only to the extent that it drives a change in a yield-limiting variable. This may be explained by research from multiple systems showing that the relationship between soil health properties—such as total carbon—and crop yield can be positive<sup>23,31</sup>, saturating<sup>32,33</sup> or even negative<sup>34</sup>. In addition, although we have shown measurable changes in soil health indicators over a relatively short time period from a soil science perspective, and although showing changes over the short term can be valuable for decision-makers, the potential of these changes to motivate farmer adoption may be limited by their small magnitude, their lack of clear ties to agronomic and environmental outcomes, and/or a combination of farmer time discount rates and relatively slow accrual of soil health benefits from a management perspective. This suggests the need to focus additional research on other potential short-term agronomic benefits of cover crops that may not be reflected in soil health indicators, such as their potential contribution to weed suppression or water infiltration. Thus, there is opportunity and need for further assessment of how real-world use of practices such as cover crops translate into tangible agronomic and environmental targets.

## Methods

**On-farm trial.** To assess the impact of cover crops on soil health properties (see the description of soil properties below), we analyse a dataset comprised of 1,522 soil samples collected between 2015 and 2019 from 78 farms. All farms were engaged in cover crop strip trials as part of the SHP farmer network between 2014 and 2019 and sampled for soil health indicators at least twice. The SHP enrolled the first of these farms in 2014 and has since added more than 100 strip trials each year on a rolling basis. (Fig. 1). In the first year of farm enrolment, an SHP field manager worked with the farmer to select a field for the trial and the management practice or system to be trialled, to design the trial, and to create georeferenced maps of the trial layout and of points to be soil sampled. For the cover crop trial we report in this paper (93% of all SHP farms trialled cover crops), the management history before trial implementation was consistent across the field, and a cover crop was added to the treatment strips. Trials require at least a 30-acre field (to obtain at least a 20-acre minimum plot size), and the most common layout was an 8-strip format ( $n=4$  for each treatment). The treatment strips were typically alternated between treatment and control across the field.

**Soil sampling.** Baseline soil sampling occurs in the first spring following enrolment, and the implementation of the first treatment occurs the subsequent autumn. Soil health sampling was targeted every other year thereafter. However, for some farms, the first soil sample was not collected until after the first year of cover cropping. Furthermore, on some farms, soil samples were sometimes collected in consecutive years rather than every other year (for example, 2015, 2016 and 2018). Soil sampling occurred in the early spring before planting, and samples were collected by farmers' agronomists, a contract soil sampler or an SHP field manager using protocols and sample shipping materials provided by the SHP.

Using the map and shapefile of predetermined sample points, the soil sampler used a Global Positioning System to navigate to each sample point (laid out in a 1-acre grid over the strip trial; see Supplementary Fig. 2). At each sampling point, at least 12 soil cores of 15 cm were collected with a 2-cm soil probe in a 30-foot circle around the point. Soil was placed in a 5-gallon bucket and combined with the soil from the rest of the sample points within a strip to create a single, composite soil health sample over two or more soil sample points. For an 8-strip trial, this means that 8 composite soil health samples were subsequently shipped on ice to Cornell University where the comprehensive assessment of soil health (CASH) was performed.

**Soil health measures.** This assessment consists of multiple physical, chemical and biological soil indicators using standard methods<sup>35</sup>. We focus on the physical and biological measures of soil health: active carbon, aggregate stability, ACE soil protein, available water capacity, respiration and total soil organic matter. The

CASH test also includes soil chemical measures; however, we chose not to analyse these because we were not able to appropriately control for whether a soil sample was collected before or after fertilizer application in the spring or what fertilizer was applied over time. We expected that this would have the strongest impact on soil chemical properties and thus chose to omit those factors from analysis. The CASH test provides an aggregate soil health score that is an average of the individual tests. As a result of literature highlighting potential uncertainties about how to interpret this score<sup>30</sup>, changes in how the scoring has occurred over time<sup>36</sup> and other literature questioning the value of aggregate indices when underlying ecological processes respond to different drivers<sup>37,38</sup>, we chose to not analyse the aggregate score. Patterns in the normative scores provided for each individual indicator were identical to patterns in the indicators themselves, so we chose to report only the data on the indicators.

All laboratory measurements were performed on soils that were air-dried and sieved to 2 mm. Moisture corrections for air-dried soils were performed by determining the mass difference between air-dried soils and soils that were oven-dried overnight at 105 °C. Soil texture was measured following Kettler et al.<sup>39</sup>. Briefly, a known mass of soil was dispersed in 3% sodium hexametaphosphate and sequential sieving and sedimentation was used to separate particle size fractions. Aggregate stability was measured using a modified rainfall simulator method<sup>40</sup>. Approximately 30 g of dry soil aggregates was placed on a 0.25-mm sieve. Samples received 12.5 mm of 4-mm drops of water over 300 s. The mass of the soil that passed through the sieve was determined by capturing this fraction, drying it at 105 °C and weighing it. The proportion of the initial soil mass that did not pass through the sieve is considered the stable aggregate fraction. Available water capacity was calculated as the difference between soil water content at field capacity and permanent wilting point. Following Reynolds and Topp<sup>41</sup>, saturated soil samples were equilibrated to  $-10$  kPa (field capacity) and  $-1,500$  kPa (permanent wilting point) for 7 days on pressure plates in air chambers. Soil organic matter was estimated through loss on ignition using a muffle furnace at 500 °C for 24 h (ref. 42). Soil organic matter content was calculated as the percentage change in mass before and after the muffle furnace (%LOI) in the following formula:  $\%OM = (\%LOI \times 0.7) - 0.23$ . A subset of samples from 2018 and 2019 were reanalysed in 2020 because of concerns from the Cornell laboratory about data quality for these samples when they were first run. Active carbon was measured after oxidation with a dilute (0.02 M) potassium permanganate ( $Kmno_4$ ) solution. A mass of 2.5 g of soil was mixed with 20 ml of the  $Kmno_4$  solution and shaken at a 120 r.p.m. for 2 min and then allowed to settle for 8 min. An aliquot was extracted and diluted before measurement on a handheld spectrophotometer and converted to units of milligrams of carbon per kilogram of soil following Weil et al.<sup>43</sup>. Respiration was measured as soil heterotrophic respiration over a 4-day incubation period following Haney and Haney<sup>44</sup>. The amount of  $CO_2$  was determined as the change in electrical conductivity of a KOH solution measured with a conductivity cell<sup>44</sup>. Soil protein was determined through extraction with sodium citrate<sup>45</sup>. Extracts were shaken for 5 min at 180 r.p.m. and heated to 121 °C in an autoclave for 20 min. After cooling, an aliquot was extracted and centrifuged for 3 min. The quantity of protein was measured with colorimetry in a 96-well plate and calibrated to standard concentrations of bovine serum albumin. Soil pH was measured in a 1:1 solution of soil to water using a desktop pH meter.

**Statistical analysis.** To assess the impact of farm management, we regressed each soil health indicator against a dummy variable for whether a sample was collected from a cover crop control or treatment strip (treatment = 1, control = 0); the number of years that farm has been implementing the experiment; the specific year of the dataset; and the percentage of clay and silt as proxies for soil type. We fitted separate intercepts for each farm to capture farm-specific information not controlled for by variables that do not vary by strip and/or year<sup>46</sup>. Since farms joined the SHP in each year from 2014 to 2019, the data comprise an unbalanced panel, with differing number of years of treatment for farms depending on when they joined. Furthermore, because this is a farmer-led experiment, there are farm-level differences in tillage and the details of cover crop management that need to be controlled for. However, tillage practices were consistent between trial and control strips on a given farm. Half of farmers planted a single cover crop species and 80% of these farmers planted cereal rye. For tillage, approximately half of farms used no-till, 10% of farms used conventional tillage and the remaining used other versions of conservation tillage such as reduced tillage and strip tillage. We transformed independent variables by centring binary variables and subtracting the mean from quantitative variables followed by dividing by two standard deviations<sup>47</sup>. Doing this allows the comparison of the effect strength of predictor variables that would otherwise be on different scales. Thus, a variable with a coefficient two times greater than the coefficient for another variable can be interpreted as having twice as strong an impact on the response variable. As a result of the unbalanced panel, we chose to fit a model to the overall dataset as well as separate models for each year in the dataset. We fitted separate models for each year to ensure that any long-term trends were not being masked by year-to-year variation. We also removed farms with fewer than two samples (baseline sample plus at least one post-baseline observation). This produced a dataset with 1,522 soil observations from 78 unique farms collected between 2015 and 2019. Models were fitted with the lme4 package<sup>48</sup> in the R statistical software<sup>49</sup>. We report coefficient



estimates, standard error and  $P$  values as well as model  $R^2$  for both the fixed effects alone and the fixed effects plus the farm-specific intercepts.

The soil organic matter model was fitted with Hamiltonian Monte Carlo estimation in the Stan language with Rstan<sup>50</sup>. We did this to allow for an informed prior estimate of the relationship between clay and carbon, which has been quantified for the USA<sup>51</sup>. Priors are necessary to compute parameters using Bayesian methods<sup>52</sup>. In cases where there is no prior knowledge of a relationship, users select uninformed priors such that parameter estimates are generated entirely by the collected data. In our case, we chose to benefit from the well-understood relationship between soil carbon and clay to provide prior information to the parameter estimation process. To do this, we subset data on soil carbon and clay from Rasmussen et al.<sup>51</sup> for the states in our dataset. Since the data from Rasmussen et al.<sup>51</sup> are reported on a per-horizon basis, we filtered out observations that were from horizons deeper than 30 cm, calculated horizon size in centimetres and aggregated per-horizon soil carbon values as a weighted mean, weighted by horizon depth. As the Rasmussen data report soil carbon, rather than organic matter, we converted carbon to organic matter by multiplying by 1.8 following Howard and Howard<sup>53</sup>. As a result of a log-normal distribution of organic matter, we regressed the log of organic matter against the percentage of clay, which we transformed as described for the other models above (Supplementary Table 9). We were conservative in generating our model prior estimate by doubling the standard deviation of the coefficient estimate (Supplementary Table 9). This ensures that the final parameter estimate is based on both the prior and the observed data. For the soil organic matter models, we report the credible intervals of the parameter estimate. Overall model goodness-of-fit is documented with posterior predictive tests that evaluate the overlap of data generated from the estimated model with the observed data<sup>52</sup> (Supplementary Fig. 3).

### Data availability

The data have not been made publicly available because of a data privacy and use agreement with members of the SHP. Some parts of an aggregated dataset may be available upon request.

### Code availability

Code and regression model objects are available through GitHub at <https://github.com/swood-ecology/soil-health-partnership>.

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## Author contributions

S.A.W. and M.B. designed the research; S.A.W. conducted the analysis; S.A.W. wrote the first draft of the paper; S.A.W. and M.B. finalized the paper.

## Competing interests

The authors declare no competing interests.

## Additional information

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