Scaling up agricultural conservation: Predictors of cover crop use across time and space in the U.S. upper Midwest

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Abstract: Scaling up cover crop use will increase crop diversity on agricultural lands and help achieve sustainable production and environmental wellbeing. To increase the total acreage planted to cover crops, more farmers need to use cover crops on a larger proportion of their farms (extent) and for a longer time (longevity), suggesting the importance of spatial and temporal scales of adoption. The adoption literature lacks attention to the spatial and temporal precision of practice measures and misses opportunities to identify consistent or diverse mechanisms for scaling up conservation practices. To fill this gap, we used data from 1,724 corn and soybean farms in Illinois, Indiana, Michigan, and Ohio to study three measures of cover crop usage: the use of cover crops in a single year on a specific field, the percent of acres planted to cover crops on a farm in a single-year, and years of cover crop use. Our models included key biophysical, operational, policy, social, and psychological factors. We hypothesize that predictors of cover crop adoption and intensity and longevity of use differ. Our results revealed five factors that performed consistently across measures (perceived benefits of cover crops, knowledge, profitability goals, no-till, rotational diversity), while the effects of the other seven factors varied, including sustainability goals that were only associated with the longevity of use. Policy programs that aim at increasing cover crop use should consider which aspect of scaling-up is being targeted, then focus on corresponding factors that can better tailor policy and education programs to farmer motivations and decision-making contexts.

Keywords: practice adoption-farmer decision-making-scale-corn belt

Scaling up agricultural conservation is critical for the transition of the U.S. agricultural landscape from a specialized production system to a more diversified system that serves multiple ecological, economic, and social functions (Dosskey et al. 2012, Robertson et al. 2014, Prokopy et al. 2020). Cover crops are plant species grown between seasons of cash crops. As a practice, cover crop use increases crop diversity while offering a range of agronomic benefits like limiting soil erosion, controlling weeds, reducing fertilizer input, and building soil organic matter (Robertson et al. 2014, Wallander et al. 2021). Using cover crops can also reap various environmental benefits, such as reducing nutrient leaching, sequestering carbon, and increasing resilience against wind erosion and extreme weather events (Snapp et al. 2005, Abdalla et al. 2019, Robertson et al. 2022). Given these benefits, cover crop use is considered a high-potential environment management strategy for sustainable production and environmental wellbeing (Wallander et al. 2021, Yoder et al. 2021).

Policy interest and support for cover crops have increased at the national, regional, and state levels. In 2017, a total of $180 million of financial incentives were provided through federal and state policy programs such as the Environmental Quality Incentives Program (EQIP) and the Conservation Stewardship Program (CSP) to encourage the adoption of cover crops (Wallander et al. 2021). In the fiscal year 2022, the Natural Resources Conservation Service (NRCS) launched a new cover crop initiative in 11 states that provided $38 million to help farmers implement the practice (USDA-Natural Resources Conservation Service 2022). Many state-level programs also exist. For example, Ohio pays 12 to 40 dollars for each acre that is planted to cover crops for targeted areas (Wallander et al. 2021). These policies and initiatives demonstrate a widespread institutional interest in increasing cover crop adoption.

However, the total acreage planted in cover crops (15.4 million acres; 6.2 million hectares) is still markedly lower than the acreage planted to corn and soybean (174.9 million acres; 70.8 million hectares), according to the 2017 Census of Agriculture administered by the U.S. Department of Agriculture (USDA) National Agricultural Statistics Service (USDA-National Agricultural Statistics Service, 2019ab). It is also far lower than the total acres under no-till (104.5 million acres; 42.3 million hectares), another conservation practice that reduces the disturbance of soil and improves soil health (USDA-National Agricultural Statistics Service 2019b, Wallander et al. 2021). Indeed, the potential of increasing cover crop use spatially, and lengthening cover crop use on single fields is substantial. Scaling up cover crop use will be particularly beneficial for the U.S. Midwest (Basche and Roesch-McNally 2017). The region specializes in corn and soybean production and has experienced nutrient runoff and water quality problems, such as harmful algal blooms in the Great Lakes (Michalak et al. 2013, Guo et al. 2021). Increasing uptake of cover crops or scaling up cover crop use is an important component of the solution (Abdalla et al. 2019, Pannell and Claassen 2020, Church et al. 2020).

Diversifying the conceptualization of adoption

To support ongoing policy and educational efforts, advancement in social science research on conservation adoption is needed. Here, we highlight the need to diversify the conceptualizations of adoption and associated measurement to better capture the complexities of real-world behaviors and their impacts and causes (Reimer et al. 2014, Ulrich-Schad et al. 2017). Cover crop use is typically measured as a binary, discrete variable, asking whether a farmer has ever used cover crops or in a specific year (Singer et al. 2007, Arbuckle and Roesch-McNally 2015). Missing from this approach are measures of cover crop use intensity (or extent) and longevity (sustained change). Pannell and Claassen (2022) emphasized sustained adoption over

time and the extent of adoption in determining potential benefits of a proposed program and suggested a set of nuanced and descriptive terms, such as full adoption, partial adoption, extent of adoption, and continuous adoption. Reimer et al. (2014) called on conservation researchers to be more precise in specifying temporal and spatial contexts of adoption. Thompson et al. (2021) highlighted the need to look beyond dichotomous measures and examine the intensity of cover crop implementation. More attention to the extent and longevity of the use of cover crops, in addition to adoption, is needed to comprehensively describe the extent of adoption within a farm as well as continuous adoption or persistence.

In a single year, farmers make many decisions including whether they will plant cover crops in a single field, how many acres of their operation will be planted with cover crops, and which cover crop (e.g. species or mix) will be planted. A single-year binary measure of cover crop adoption used alone, while important, misses information on whether the farmer will use cover crops on a large portion of their land and whether they will sustain their use in subsequent seasons. A farmer who uses cover crops sporadically in their crop rotation cycle or on a small portion of their land may have lower equipment requirements, accumulate fewer experiences in managing complex crop systems, and have less impact on their fields and surrounding landscape compared to farmers who have used cover crops for a long time and on a large proportion of acres of their farms. Missing such spatial and temporal details will limit the capacity to assess whether a certain adoption level (measured in the number of farmers) will generate sufficient benefits at broader scales, which is an important question for researchers and practitioners (Ulrich-Schad et al. 2017).

Promoting cover crop use by more farmers, on more acres, and in more years is therefore crucial for many sustainability goals—in other words, scaling up across all three dimensions is

92 necessary. While studies that use binary measures of cover crop adoption capture the factors that
93 influence farmers to adopt, providing valuable information about how to scale up adoption by
94 reaching more farmers, they fail to include analyses that inform us about scaling up across time
95 and space. Here, we aim to address all three dimensions, and investigate whether the factors that
96 previously have been shown to be influential on initial adoption of cover crops are also
97 influential on the number of acres and number of years of use. The investigation is motivated by
98 the concept that relationships and patterns apparent with one measurement strategy or at one
99 scale may not manifest when viewed from other scales, and the profound impacts of considering
100 scales in study design and analysis (Hewitt et al. 2017). Such an investigation requires the
101 incorporation of novel levels of measurement to the practice adoption literature. The proportion
102 of a farm's total acres planted to cover crops tells us about the spatial extent of adoption, referred
103 to here as intensity (or extent). The number of years cover crops have been planted on a farm
104 tells us about the continued use of the practice over time or its temporal extent, referred to as
105 longevity. In the following sections, we first summarize factors that have been studied
106 influencing cover crop use in general, then propose how models for adoption, intensity, and
107 longevity of the use of cover crops may differ.

108 ***Factors influencing cover crop use***

109 The adoption literature has identified a range of factors explaining cover crop use and
110 other conservation practice adoption in general that includes psychological, social, policy,
111 operational, biophysical, and demographic factors, suggesting multiple mechanisms (Carlisle
112 2016, Prokopy et al. 2019). Many empirical models are implicitly or explicitly guided by the
113 proposition that farmer conservation behaviors are driven by interactions between attributes of

114 the decision-maker, the decision context, and attributes of potential conservation behaviors
115 (Epanchin-Niell et al. 2022).

116 Psychological factors include individual perception of the benefits and constraints of
117 behavior, beliefs about social norms, and fundamental beliefs related to values and identities that
118 affect individual intentional and actual behaviors. For instance, farmers can be motivated to
119 adopt cover crops by perceived soil and environmental benefits of cover crop use (e.g.
120 preventing soil erosion, improving soil structure, and increasing soil organic matter) (Singer et
121 al. 2007, Arbuckle and Roesch-McNally 2015, Dunn et al. 2016, Thompson et al. 2021) and by
122 perceived efficacy (Beetstra et al. 2022), but discouraged by cost and information barriers to new
123 practices and other economic considerations (e.g., new equipment, input cost, lack of
124 information, the uncertainty of benefits) (Plastina et al. 2018b, 2018a, 2018c, Roesch-Mcnally et
125 al. 2018, Sawadgo and Plastina 2021, Sawadgo et al. 2021, Beetstra et al. 2022). Although
126 certainly important, profitability is not the only determinant of farmer decisions. Farmers appear
127 to act on noneconomic motives, including their goals to be a steward of the land, to farm
128 sustainably (Carlisle 2016, Burnett et al. 2018, Schoolman and Arbuckle 2022), and in response
129 to their social contexts (Sneddon et al. 2011). Research has shown that farmers with more
130 knowledge and who have more access to information are considered more likely to use
131 conservation practices (Arbuckle and Roesch-McNally 2015, Carlisle 2016).

132 In addition to farmers' thoughts and motivations, farm operational characteristics, policy,
133 social context manifested as information exchange, and biophysical factors also play a role.
134 Farms already managed with other conservation practices such as conservation tillage, extended
135 crop rotation, and integrated with livestock production are more likely to use cover crops (Singer
136 et al. 2007, Arbuckle and Roesch-McNally 2015, Plastina et al. 2018b, 2018a, 2018c, Lee and

McCann 2019, Luther et al. 2020, Sawadgo et al. 2021). Regarding policy mechanisms, cost-share programs and incentives are believed to be positively associated with higher adoption rates (Singer et al. 2007, Dunn et al. 2016, Lee and McCann 2019, Luther et al. 2020), while crop insurance is considered to complicate their decisions (e.g., some cover crop practices may result in the loss of crop insurance coverage) and thus decrease adoption rates (Fleckenstein et al. 2020, Connor et al. 2021). Information is considered essential in conservation, as farmers need to be aware of the practices and their benefits before they would consider adoption (Wojcik et al. 2014, Epanchin-Niell et al. 2022). Biophysical factors such as steeper field slopes are less tested in empirical models but are believed to be influential in farmer decisions given the close tie between ecological and social systems within agricultural contexts (Lee and McCann 2019).

Farm characteristics, such as farm size and land tenure, and farmer characteristics, such as years of farming and education levels, are also associated with farmer decisions (Carlisle 2016, Sawadgo et al. 2021), and should be included as controls in a baseline or standardized model of adoption (Prokopy et al. 2019). However, because studies differ in whether they included these controls in their adoption models, it is unclear which farm and farmer characteristics constitute key controls. Studies have examined farm size, land tenure, farmer education levels, and age as important characteristics, but the results are inconsistent. For example, land tenure, whether the farmer rents or owns the land, is conceptualized to affect conservation behaviors through different lease types and the different levels of land tenure security and autonomy (Sawadgo et al. 2021). However, the relations do not always stand. While Sawadgo et al. (2021) and Lee and McCann (2019) found cover crop use is lower on rented land, Singer et al. (2005), Arbuckle et al. (2015), and Dunn et al. (2017) found no significant relationship between cover crop use and land tenure.

(In)Consistent effects on adoption, intensity, and longevity of uses of cover crops

In general, we expect different psychological, social, policy, operational, biophysical, and demographic factors to shape cover crop adoption, intensity, and longevity of use, because initial, expanded, and sustained uses require different levels of effort and resources and thus face different field and farm level and structural barriers (Pannell and Claassen 2020, Reimer et al. 2021). The risks in each adoption dimension differ, as those who are trialing the practice on a small portion of their land may need to face a lower level of risk compared to those who are deciding whether they should invest significantly more to plan all their land to cover crops (Pannell et al., 2006). As the stakes of decisions differ, how farmers view the benefits and costs of cover crop use and the weights of various contextual factors for their decisions (suitability of the land and existing farm operations, availability of information) may differ. A farmer who trials cover crops in a single field may need to worry less about how the practice will affect yields. The added seed and operational costs may be few and do not occupy the center of decision-making. In comparison, farmers who use cover crops on a large portion of their land will need to work with increased operational costs and higher risks on total yields. Using cover crops every year may require more determination and skills to fit cover crops to planting and market conditions that change from year to year, but the long-term benefits of cover crop use may reveal benefits such as improved soil quality and reduced input cost. Incentives may encourage more farmers to try cover crops on a field but may not necessarily translate into sustained use, especially when the incentives cease (Pannell et al., 2020). Farmers' decisions of continued use despite risks and barriers may signal valuing the practice's environmental benefits fits such as reduction in soil erosion and soil health improvement more than its economic return (Plastina et al., 2018). Because the behaviors of using cover crops (including trial and continued

use), using cover crops over large areas in the present, and using them over long periods are different, we expect the models for adoption and intensity and longevity of use are different. The question is to what extent these models differ.

Few studies have examined adoption and intensity and longevity of use simultaneously, but an exception comes from Thompson et al. (2021) who found that the factors associated with initial adoption were noticeably different from those associated with the intensity of use. For example, they found that lack of equipment/technology and belief that cover crops reduce loss of nutrients into waterways were associated with initial adoption but not with the intensity of use, whereas belief about cover crops reducing heat stress of crops and adding new technologies to reduce risks associated with intensity but not initial adoption. On the contrary, a lack of proven benefits is negatively associated with both initial adoption and intensity, suggesting the potential primary effect of profit-related attitudes, meaning consistently affecting cover crop use at different scales. However, that study did not include other psychological factors such as values and knowledge, or biophysical and policy factors. Dunn et al. (2016) studied three outcomes including the proportion of operated land planted to cover crops in 2013, whether the practice was self-funded, and whether the farmer discontinued cover crop use. They found some differences in predictors between the proportion of land in cover crops and discontinued use of cover crops. For example, finding trial and error to be an effective learning strategy was not associated with the amount of land in cover crops, but was negatively associated with discontinuance of the practice—suggesting that this learning approach may assist with scaling up cover crops temporally but not spatially. However, the question remains about whether such differences may occur for other predictors of interest.

205 The adoption literature noted inconsistent findings about psychological factors, which
206 provides preliminary evidence in support of our comparison. For example, Prokopy et al. (2019)
207 found that perception, preference, and opinions about programs and practices have the
208 anticipated effects on behaviors in only about one-fourth of the empirical models (25.9%)
209 included in their comprehensive review article, pointing out different measurement strategies as
210 one of the explanations. The percentage dropped to 9.5% for environmental attitudes, suggesting
211 even less consistent effects.

212 For the biophysical characteristics of a field and a farm, the typology of a field relates to
213 yet differs from the typology of a farm, which may affect the management of a single field and
214 the whole farm differently. These factors have specific spatial and temporal boundaries. But
215 operational factors that form the decision context may consistently affect adoption, intensity, and
216 longevity of use. For example, using no-till was associated with cover crop adoption (binary
217 measure) (Lee and McCann, 2019; Thompson et al., 2021) and intensity of implementation
218 (Thompson et al., 2021). The number of crops a farm manages and having livestock was also
219 found to be associated with different binary measures of adoption, such as cover crop use ever in
220 the past (Singer, et al., 2005; Lee and McCann, 2019), on their farm in a single year (Arbuckle et
221 al., 2017), and on soybean fields in a single year (Lee and McCann, 2019).

222 Policy factors such as crop insurance and conservation programs also comprise important
223 decision contexts. They may consistently affect adoption and intensity of use, but their effects on
224 longevity will depend on when and where adoption is measured, as policy programs often have
225 start dates, end dates, and modification dates for different regions. Supporting our expectation
226 that policy factors affect adoption, intensity, and longevity of use differently, Connor et al.
227 (2021), Fleckenstein et al. (2020), and Thompson et al. (2021) all studied the effects of crop

insurance, but Connor et al. (2021) measured crop insurance in acres, Fleckenstein et al. (2020) measured crop insurance using a binary survey question, and Thompson et al. (2021) measured whether farmers thought that crop insurance limited their ability to implement cover crops. Connor et al. (2021) found crop insurance coverage to be negatively associated with cover crop acreage, while Fleckenstein et al. (2020) and Thompson et al. (2021) found that crop insurance requirements were not a barrier to farmers' adoption of cover crops (measured by binary variables).

Research question.

This study will address the following question: *Which factors predict adoption, intensity, and longevity of cover crop use?*

Addressing this research question requires a data structure that considers the varying temporal and spatial scales of cover crop use. In this study, we use three cover crop use measures, including 1) single-year cover crop use on a specific field, 2) single-year percent of acres planted to cover crops on the farm, and 3) years of cover crop use, which assess adoption, intensity, and longevity, respectively. We compare predictors associated with these three measures of cover crop use on U.S. upper Midwest corn and soybean farms using three generalized linear models.

Materials and methods

Study context. The U.S. Midwest is home to the 'Corn Belt' that stretches across 12 states, accounting for the majority of corn produced nationally and more than one-third of corn production globally. In our study, we focus on 4 states—Illinois, Indiana, Michigan, and Ohio—that represent the range of physical, demographic, and socioeconomic conditions of this

geographic region. Most row crop farms in this region have a corn/soy rotation. As of 2017, production from these 4 states comprised more than 55 million acres of cropland (22.3 million hectares), with 82.6% of that acreage planted to corn or soy. Specifically, 39.3% of total cropland acres across these 4 states were planted to corn, and 43.3% were planted to soy in 2017 (USDA-National Agricultural Statistics Service, 2019a).

Data collection. The data we used in this analysis was collected in 2018 from eligible row crop farmers in Illinois, Indiana, Michigan, and Ohio. To be eligible, farmers needed to be growing corn or soybeans, manage at least 100 acres (40.5 hectare), and be operating within a county having 15% or more of its total land in agricultural production. Within each state, the sample was stratified into two categories: farmers operating between 100 and 499 acres (40.5 and 201.9 hectares), and farmers operating 500 or more acres (202.3 or more hectares). The survey oversampled farmers who were operating larger farms to account for the larger areas they cover, as well as the lower response rate anticipated for this group (Weber and Clay 2013).

Our survey mailing used a modified Dillman protocol (Dillman et al. 2014), which featured a multi-wave survey-postcard format distributed to farmers from February to April 2018. Potential participants received a pre-notice postcard, followed by a mailing with a copy of the survey instrument, a cover letter, and a pre-paid, first-class business reply envelope; a postcard reminder was sent several weeks after the initial mailing. To accommodate our complex sampling design, our initial sample size was 5,807, with 2,461 questionnaires returned. This resulted in a 42.4% response rate, which roughly approximates mail surveys with similar designs (Arbuckle et al. 2013, Houser et al. 2019). Drawing from usable responses, our analyses used data from 1,724 farmers who planted corn and soybean in 2018, with 32% of our sample located

in Illinois (n=553), 31% from Ohio (n=528), 24% from Indiana (n=408), and 13% from Michigan (n=235).

Measures. We designed the questionnaire by drawing on previous research and in consultation with agronomists, ecologists, and stakeholders related to the USDA Long-Term Agroecosystem Research (LTAR) network. In this analysis, we focused on cover crop use and pertinent farm, field, and farmer characteristics. Farmers make a series of decisions related to cover crops by considering varying time and spatial scales. To reflect the multiple layers of cover crop adoption decisions, we measured cover crop use in three ways on the survey, which comprise our three outcome measures for our empirical models. At the field level, respondents were asked to identify the largest field on which they grew corn or soybeans, then answered questions such as, "During the 2016-2017 winter, did the field have a cover crop?" We recoded this measure into a dichotomous measure where 1=yes. At the farm level, respondents were asked to report information such as, "How many acres of your operation were planted in a cover crop (excluding winter wheat harvested for grain) in fall 2017?" and "How long have you been using cover crops (excluding winter wheat harvested for grain) on any part of your operation?" The proportion of acres of cover crop per farm was calculated by dividing the number of cover crop acres by the total number of planted acres, creating our measure of intensity. The third measure was coded into years of cover crop use, representing longevity. Figure 1 presents the distributions of the three measures. Panel A is the binary adoption measure. Panel B shows the measure of extent. Panel C shows years of cover crop use or longevity.

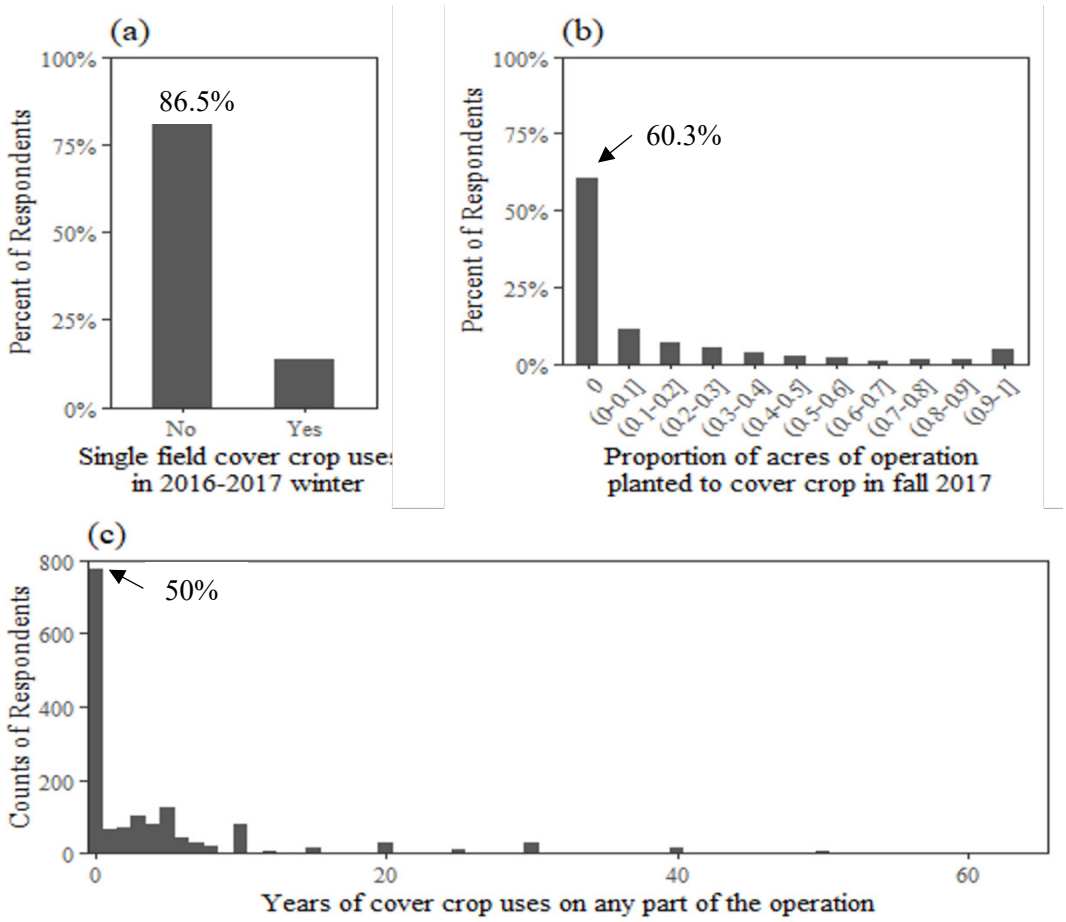

Figure 1. Distribution of cover crop measures (a) single year field level cover crop use (b) single year farm level cover crop use (c) years of cover crop use

We measured numerous field, farm, and farmer characteristics that make up the heterogeneity in farmer decisions. These independent variables can be grouped into five categories, including psychological, policy, social, operational, and biophysical factors (Prokopy et al. 2019, Yoder et al. 2021). The survey questions for all independent variables are listed in Table 1 and Supplementary Table S1.

Table 1. Survey questions for independent variables

Question	Range
Perceived benefits of cover crops	
Even if you have never planted them before, how useful do you think winter cover crops are for each of the following?	1=low to 5=high
Knowledge about cover crops	
How much do you feel you know about the following?	1=nothing at all to 5=a great deal
Profitability & Sustainability Farming goals	
When you think about being a farmer and managing your operation, how important are the following to you?	1=not at all important to 5=very important
Cost & Information-related barriers	
To what degree do you consider these factors as barriers that might discourage you from adopting new management practices?	1=not a barrier to 5=strong barrier
Information source use	
When seeking information about new agronomic practices and land stewardship issues, how frequently do you consult the following sources?	1=never, 2=once a year, 3=once a month, 4=once a week, 5=daily; collapsed into a binary variable in the analysis, 1=yes, 0=no
Farms having crop insurance in 2017	
How many of your acres planted in corn and soybean were covered under a crop insurance policy in 2017	Write-in acres; collapsed into a binary variable in the analysis, 1=yes, 0=no
Farms that participated in a federal, state, or local conservation program	
Is any land you own enrolled in any federal, state, or local conservation program? Please do not include any land required to be in conservation compliance.	1=yes, 0=no
No-till field	
What kind of tillage did you perform on this field prior to the 2017 growing season?	Fields that had no soil disturbance and with all residue left on surface in spring and fall were considered no-till. 1=yes, 0=no
No-till operation	
Do you consider yourself a no-till farmer/operation?	1=yes, 0=no
Rotational diversity – farms that planted another crop than corn or soybeans	
In 2017, how many acres did you plant of the following crops?	Write-in acres for corn, soybean, wheat, and other crops. Coded into a binary variable in the analysis, 1=yes, plant another crop than corn or soybeans, 0=no

Farms with more than 10% of revenue from livestock	
Which of the following farm products accounted for more than 10% of your farm revenues in 2017?	1=Field or grain crops, 2=fruit, nut & veg crops, 3=flowers, ornamentals & live plants, 4=milk and dairy products, 5=livestock, 6=other. Collapsed into a binary variable in the analysis, 1=yes, livestock or milk and dairy products accounted for more than 10% of the farm revenue, 0=no
Field classified as erodible	
Has any part of this field been classified as 'highly erodible'?	1=yes, 0=no
Soil texture	
How would you describe the main soil texture of this field?	Silty loam and silt; clay, clay loam, loam; sandy loam; sandy
Years of farming	
In what year did you become the primary decision maker for crops on this farm?	Write-in year
Education	
Which category best describes your formal years of education?	Less than high school, high school, some college, bachelor's degree or higher; collapsed into a binary variable in the analysis, 1=with degree higher than high school, 0=no
Field size	
How many acres is this field?	Write-in Acres
Farm tenure	
In 2017, how many acres of cropland did your operation own?	Write-in Acres

Five of the six psychological predictors were measured using average composite scores, except knowledge, which was measured as a single item (for items in each scale, see Supplementary Table 1). For each of these composite scores, we conducted reliability analyses using Cronbach's alpha to check their consistency, then performed exploratory factor analysis to check the number of common factors. Four of the five scales produced a Cronbach's Alpha over 0.7, except for cost-related barrier beliefs, which had a Cronbach's alpha of 0.68 (Supplementary Table 1). The mean of the items was used as the variable score. All psychological independent variables were measured on a five-point scale.

For other predictor categories, five independent variables were binary measures, including whether no tillage was used on the field in both spring and fall, whether the farm was a no-till operation, whether the operation received more than 10% of revenue from livestock, whether the farm participated in a federal, state, or local conservation program, and whether the field was classified as erodible. Six independent variables were transformed from continuous to binary to reduce collinearity and improve model fit, including crop diversity (planted another crop other than corn or soybeans), participation in crop insurance, whether they received information from any public source, private sources, or other farmers, and education (having an associate or college degree in addition to a high school diploma).

Modeling. We selected the appropriate model for each outcome variable based on their characteristics. For the dichotomous field-level cover crop use variable, our first outcome variable, we selected binary logistic regression. For the second outcome variable, the proportion of farm acres planted to cover crops, we relied on diagnostic checks to choose a quasibinomial regression. Our third outcome variable, years of cover crop use, was treated as count data with many zeros. We used negative binomial regression, which resulted in a good model fit, given that negative binomial regression works better with over-dispersed data.

We used multiple imputation for missing data in most predictors to preserve sample size. Imputation and modeling were completed in R 4.1.1 using packages MASS, mice, prediction, and ResourceSelection. For all imputed datasets, each model passed the Hosmer-Lemeshaw tests (for binary and quasi-binomial regression insignificant chi-squared) or the likelihood test (for negative binomial model). Goodness-of-fit tests were conducted for individual imputation datasets. For each model, five datasets were created. All models passed the goodness-of-fit test. The McFadden R^2 was 0.24 for the field model, 0.42 for the farm model, and 0.24 for the years

model. Technical details on modeling and imputation are provided in the supplementary materials.

Results

Sample description. Respondents included in the sample all self-identified as the main decision-maker for crop management on their farm. The sample is nearly all male (99%) and slightly older (mean age is 61 years) than the agricultural population targeted by the Census of Agriculture (average ages range from 55.5 in Indiana to 58 in Illinois) (USDA-National Agricultural Statistics Service, 2019c). The descriptive statistics for farmer, farm, and field characteristics are presented in Table 2. Approximately 57% of the respondents have some college or college degree. Farmers in our sample have planted cover crops on some part of their operation for an average of 4.6 years, with 65 years revealed as the longest period of cover crop use. Fifty percent of respondents reported never using cover crops.

The average farm size is 690 acres (279.2 hectares). On average, each farm had 14% of their acreage planted to cover crops in the 2016-2017 winter, with 60% of farms having zero acres of cover crop acres. A majority of farms had crop insurance for their corn and soybean acreage in 2017 (81%) and less than half of farms participated in any kind of conservation program (42%). Less than half of the farms self-identified as a no-till operation (38%), had a crop other than corn or soybeans as part of their rotation (43%), or generated more than 10% of their revenue from livestock (19%).

Based on the information reported by the respondents, the average field size for their largest field planted to corn or soybeans is 101 acres (40.9 hectares). About 14% of the fields were planted to cover crops in the 2016-2017 winter. Sixteen percent of the fields were classified

357 as highly erodible, and 33% were reported to be no-till. Most of the fields were reported to have
358 a "somewhat sandy" soil texture (53%), which includes clay, clay loam, and loam soil types;
359 only 2% were reported as being sandy.

Table 2. Descriptive statistics for farm, field, and farmer characteristics

Variable	Unit	Mean	S.D.	Min	Max
Percent of fields planted to a cover crop in 2016-2017 winter	0/1	0.14	-	0	1
Proportion of acreage within a farm planted to cover crop in fall 2017	Proportion	0.14	0.27	0	1
Length of cover crop use	Number	4.6	8.8	0	65
Perceived soil health benefits of cover crops	Number	3.77	0.75	1	5
Knowledge about cover crops	Number	3.05	1.02	1	5
Profitability farming goals	Number	4.00	0.72	1	5
Sustainability farming goals	Number	4.38	0.56	1	5
Cost-related barriers	Number	3.40	0.80	1	5
Information related barriers	Number	2.55	0.85	1	5
Received information from public sources	0/1	0.86	-	0	1
Received info from private sources	0/1	0.96	-	0	1
Received info from other farmers	0/1	0.87	-	0	1
Have crop insurance	0/1	0.81	-	0	1
Participated in a federal, state, or local conservation program	0/1	0.42	-	0	1
No-till field	0/1	0.33	-	0	1
No-till operation	0/1	0.38	-	0	1
Planted another crop than corn or soybeans	0/1	0.43	-	0	1
More than 10% of revenue from livestock	0/1	0.19	-	0	1
Fields classified as erodible	0/1	0.16	-	0	1
Soil texture-least sandy	0/1	0.21	-	0	1
Soil texture-somewhat sandy	0/1	0.63	-	0	1
Soil texture-much sandy	0/1	0.13	-	0	1
Soil texture-most sandy	0/1	0.02	-	0	1
Illinois	0/1	0.32	-	0	1
Indiana	0/1	0.24	-	0	1
Michigan	0/1	0.14	-	0	1
Ohio	0/1	0.31	-	0	1
Farming experience (years)	Number	32.58	14.24	1	71
Education: have degree more than high school	0/1	0.57	-	0	1
Field size (acres)	Number	100.72	104.55	5	3015
Farm size (acres)	Number	690.05	654.84	100	7063
Proportion of acres owned by the farmer	Number	0.63	0.35	0	1

360

Modeling results. At the field level (Model 1, Table 3), we found that farmers who perceive benefits from cover crops (0.89) and who reported high knowledge of cover crops (0.88) were more likely to use cover crops on the field reported, but farmers who reported a stronger economic motive with strong profitability goals were less likely to use cover crops on the reported field (-0.43). No-till fields (0.67) and those being classified as highly erodible (0.54) were more likely to be planted with cover crops. Fields in farms that had crop insurance (0.48), participated in a conservation program (0.50) and with planted crops other than corn or soybeans in the last year (0.43) were also more likely to have cover crops.

Perceiving benefits from cover crops (0.74) and having knowledge of cover crops (0.89) (Model 2, Table 3) positively predicted the proportion of acres of cover crop use at the farm level. Farmers with strong profitability goals, and those who perceived cost-related barriers to adopting new agricultural technology, used cover crops on less of their operation (-0.32 and -0.17, respectively). Participation in a conservation program was associated with greater cover crop use (0.34) but having crop insurance was not (p-value=0.089). Farmers self-identifying as having a no-till operation (0.44) and with planted crops other than corn and soybeans (0.19) had greater intensity of cover crop use.

From Model 3, perceived benefits of cover crops, knowledge about cover crops, and having sustainability-oriented farming goals were associated with increased longevity of cover crop use (0.15, 0.70 and 0.26, respectively; Table 3), while those with strong profitability goals showed decreased longevity (-0.36). Participating in crop insurance was associated with fewer years of cover crop use (-0.41), while the effect of participation in a conservation program was not significant (p-value=0.16). Being a no-till operation (0.24), planting crops other than corn

and soybeans (0.57), having more than 10% of revenue from livestock (0.57), and having a field that is classified as highly erodible (0.25) were all associated with longevity of use.

Across the three models, five factors were consistently significant, including three psychological factors - perceived benefits of cover crops, knowledge, profitability goals, and two operational factors - no-till (at the field or farm level), and rotational diversity (planted another crop other than corn or soybean). To understand the practical importance of the consistent factors and compare their effects across models, we calculated the predicted probability for each of the five variables with all other variables held at their means or modes. For example, Illinois has the most cases in the sample (is the mode for the state variable), and the predicted probability for high versus low knowledge is calculated for residents in Illinois and with other variables held at their mean or mode.

Knowledge's increasing effects on the probability of adopting cover crops stand out (Table 4). For example, a farmer who rated their knowledge about cover crops at the lowest level, had a predicted probability of using cover crops on a single field of 0.007, compared to farmers who rated their knowledge at the highest level with a predicted probability of 0.182 (Table 4). In comparison, a farmer who considered cover crops to have low soil health benefits, with all other variables held at their means or modes, had a predicted probability of using cover crops on a single field of 0.004, compared to farmers who considered cover crops to have high soil health benefits having a predicted probability of using cover crops on a single field of 0.111. Regarding profitability goals, results show decreased probability; the strongest profitability goals decreased the probability of cover crop use on a single field to 0.027, compared to the probability of 0.127 for those with the weakest profitability goals. Knowledge's effects were also observed at the farm level and for years of cover crop use.

Table 3. Modeling results

	Model 1	Model 2	Model 3
Outcomes	Adoption	Intensity	Longevity
Intercept	-8.49 ***	-8.49***	-2.78***
Psychological factors			
Perceived soil health benefits of cover crops	0.89***	0.74***	0.15*
Knowledge about cover crops	0.88***	0.89***	0.70***
Profitability farming goals	-0.43**	-0.32***	-0.36***
Sustainability farming goals	0.09	0.16	0.26**
Cost-related barriers	-0.09	-0.17*	0.03
Information related barriers	0.03	0.09	0.01
Social factors			
Received information from public sources	0.56	-0.11	0.12
Received information from private sources	-0.71	0.24	0.11
Received information from other farmers	0.24	0.22	0.14
Policy			
Have crop insurance	0.48*	0.27	-0.41**
Participated in a federal, state, or local conservation program	0.50**	0.34***	0.16
Operational factor			
No-till field	0.67***	-	-
No-till operation	-	0.44***	0.24*
Planted another crop than corn or soybeans	0.43*	0.19*	0.57***
More than 10% of revenue from livestock	-0.26	0.12	0.57***
Biophysical factors			
Field classified as erodible	0.54**	-0.03	0.25*
Soil texture-least sandy	-	-	-
Soil texture-somewhat sandy	-0.02	-0.02	0.21
Soil texture-much sandy	0.30	0.35*	0.18
Soil texture-most sandy	0.63	-0.53	0.54
Illinois	-	-	-
Indiana	0.34	0.73***	-0.06
Michigan	-0.05	1.17***	0.88***
Ohio	0.25	0.71***	0.46***
Farming experience (years)	0.006	-0.02***	0.004
Education: have degrees more than high school	0.22	0.20	-0.10
Field size (acres)	0.0004	-	-
Farm size (acres)	-0.00003	-0.00008	0.0003***
Proportion of acres owned by the farmer	0.06	0.85***	0.04
Valid n	1721	1666	1529
McFadden R^2	0.24	0.42	0.24
Link	Binary	Quasi-binomial	Negative-binomial

* p-value <.05 **p-value<.01 ***p-value<.001

406 In comparison, the changes in probabilities and average years of use related to no-till
407 and rotational diversity were smaller. For example, farmers who used no-till slightly increased
408 the probability of using cover crops on a field by 0.034; farmers who planted another crop other
409 than corn and soybeans increased the probability of using cover crops on a field by 0.022.

Table 4. Predicted probability (Model 1 and 2) and predicted average years (Model 3) for consistent factors with all other variables held at their means or modes

	Model 1 Field	Model 2 Farm	Model 3 Years
Perceived soil health benefits of cover crop – weakest	0.004	0.004	0.093
Perceived soil health benefits of cover crop – strongest	0.111	0.077	1.453
Knowledge – lowest level	0.007	0.005	0.288
Knowledge – highest level	0.182	0.162	5.101
Profitability goals – weakest	0.127	0.080	3.594
Profitability goals – strongest	0.027	0.023	0.882
No-till -No	0.040	0.032	1.254
No-till - Yes	0.074	0.048	1.645
Planted another crop than corn or soybeans -No	0.040	0.032	1.254
Planted another crop than corn or soybeans -Yes	0.062	0.038	2.189

410

411 **Discussion**

412 We conducted analyses with data from 1,724 corn and soybean farms in Illinois, Indiana,
413 Michigan, and Ohio on the use of cover crops at the field and farm levels, and over years. We
414 accounted for broader contextual factors (e.g. biological conditions, economic factors, existing
415 farming systems), personal factors (e.g., attitudes, knowledge, goal orientations), and farm and
416 farmer characteristics as controls, moving toward a baseline adoption model. Although we
417 expected to see models for adoption, intensity, and longevity of cover crop use mostly differ, we
418 uncovered five factors having consistent effects across scales. These factors are perceived soil
419 health benefits of cover crops, knowledge about cover crops, profitability goals, no-till use at the

field or farm level, and rotational diversity. We found seven factors had more inconsistent effects on cover crop uses, including sustainability goals, cost-related barriers to adopting new practices, crop insurance, participation in conservation programs, livestock diversity, erodible fields, and field soil texture.

Three of the six tested psychological factors have consistent effects on the adoption, intensity, and longevity of the use of cover crops, suggesting the primary effects of these factors. Farmers who consider cover crops effective in improving soil health and have knowledge about cover crops are more likely to use cover crops, increase the acres planted to cover crops on their farms and use the practice longer. We were surprised that the effect of perceived soil health benefits was consistently significant, as Prokopy et al. (2019) noted inconsistent findings about the effects of attitudes. Conversely, strong profitability goals inhibit cover crop adoption and reduce the intensity and longevity of implementation, consistently with Thompson's et al. (2021) finding. Perceived soil health benefits may work to offset the negative effects of economic motives. Our results highlight the importance of building the perceived effectiveness to scale up cover crop use across farms, acres, and time.

As expected, two operational factors have consistent effects on adoption, intensity, and longevity of implementation, highlighting how existing management has a primary effect on individual practice decisions. Farms with diverse crop rotations are more likely to demonstrate a capacity to manage complex productions and may have more equipment, experience, and mental readiness to incorporate cover crops (Singer et al. 2007, Arbuckle and Roesch-McNally 2015, Lee and McCann 2019, Luther et al. 2020). The use of no-till is found to be positively associated with cover crop use, consistent with prior work (Lee and McCann 2019; Thompson et al. 2021). The positive association between no-till and cover crops contradicts a common belief that these

two practices are incompatible at the operation level, as many farmers report using tillage to terminate cover crops. The complementarity rather than tradeoff of no-till and cover crops may reflect the effects of system thinking on conservation practices and farmers' capacity to find other ways to reap the combined benefits of no-till and cover crops (Thompson et al., 2021).

Seven factors were found to be associated with one or two outcomes. Why they are associated with certain outcomes but do not associate with other outcomes is worth exploring. Sustainability goals only affect the longevity of cover crop use, compared to profitability goals. Schoolman and Arbuckle (2022) found that agri-environmental goals increased fruit and vegetable farmers' likelihood to grow cover crops (binary variable); however, their adoption measure differs from ours. Some researchers argue that although environmental stewardship affects many farmers' decisions, continued profitability might be an overriding concern that may help explain the absence of a consistent effect of sustainability goals across our models (Robertson et al. 2014). Since cover crops require several years of persistent use for yield and soil health benefits to manifest, soil health benefits related to long-term soil fertility may provide synergy between economic interests and environmental interests only after an extended period (Cusser et al. 2020). Farmers may be willing to consider the long-term soil health benefits over short-term economic profits, as the magnitude of the coefficients for perceived soil health benefits is larger than those for profitability goals, except for longevity of use where the combined coefficients of perceived benefits and sustainability goals were larger than the coefficient of profitability goals.

Erodible fields affect single-field decisions and accumulated adoption patterns, but not farm-level decisions. This finding intuitively indicates that field characteristics influence field-specific management decisions and can do so over time. Participation in a conservation program

466 was positively associated with cover crop adoption and extent in the study year, but not
467 significantly associated with longevity. The result is consistent with Sawadgo et al. (2022) where
468 half of their sample would be willing to increase the area of their land under conservation
469 practices that include cover crops if they could receive tax credits or deductions similar to a
470 conservation program. The result is also consistent with the work of Singer et al (2007) in
471 Indiana and Lee et al.'s (2019) study of soybean farmers. However, why was participation in
472 conservation programs not associated with the longevity of cover crop use? One potential
473 explanation is that the group of farmers who first used cover crops were innovators and were not
474 motivated by external incentives like those from federal conservation programs. The earliest that
475 one farm in our sample reportedly started using cover crops dates back six decades (i.e., was 65
476 years ago, in 1953). Federally sponsored conservation programs related to production practices
477 were not authorized until the 1990s (EQIP) and 2000s (CSP), although federal land retirement
478 programs for soil conservation have been around since the 1930s (Reimer et al., 2018). In
479 addition, conservation programs provide payments for a limited number of years, which presents
480 an "end-of-contract problem" and may prevent them from encouraging increased longevity of
481 conservation practice use (Kuhfuss et al. 2016).

482 The effect of crop insurance also differed across outcome variables. Our results did not
483 find a negative association between crop insurance and cover crop adoption (Model 1),
484 consistent with Fleckenstein et al. (2020) and Thompson et al. (2021), nor between crop
485 insurance and cover crop extent (Model 2), inconsistent with Connor et al. (2021). However, the
486 observational units differed, with counties in Connor et al. (2021), while the observational unit in
487 our study was a farm. Noticeably, farmers who currently use crop insurance, have, on average,
488 been using cover crops for fewer years. Federal crop insurance policies have only recently

489 changed to allow all insured farms to plant cover crops, which could explain this finding.
490 Interestingly, farmers' contact with public information sources, private information sources, or
491 other farmers did not produce significant associations with cover crop use across scales. It could
492 be that the binary variables of information use did not capture the content and weight of
493 individual information sources on cover crop use or that information has an indirect rather than a
494 direct effect (Walpole and Wilson 2022).

495 Our results demonstrate the benefits of studying adoption in more than one way: as a
496 binary choice, the extent of adoption within a farm, and continuous or sustained adoption.
497 Factors differ in whether they consistently or inconsistently predict adoption, intensity, and
498 longevity of implementation, which provides a new approach to identifying influential factors
499 among a myriad of possible predictors. The finding highlights the importance of considering and
500 testing whether a mechanism operates across dimensions or only on certain dimensions, which
501 will determine whether programs and policies aimed at tuning up or down the mechanisms will
502 reach the desired number of farmers, acres, and years of uses simultaneously to achieve target
503 sustainability outcomes.

504 ***Limitations and future research.*** It is worth noting that although we sought to cover
505 important categories of predictors, future research could extend our models to include other
506 potentially important predictors, including, for example, precipitation, temperature, soil
507 moisture, and risk perception. Additionally, due to the complexity of categorical outcomes, we
508 were not able to fit the models simultaneously, which would have otherwise allowed us to see
509 whether farmers' decisions about cover crop adoption were connected across different scales.
510 Some farmer, field, and farm characteristics were simplified to binary variables to reduce
511 collinearity among some predictors, which may limit the models' ability to detect their effects.

However, to our knowledge, this study remains one of the first to examine cover crop use across both spatial and temporal scales, and we are optimistic that our results highlight some important insights for both future research and policy.

We recommend future research use analytical techniques, biophysical measures, and conceptual frameworks that further our understanding of the challenges farmers face in adopting cover crops. We call for collective efforts in selecting theoretically compelling variables and striving to build a basic conceptual model for conservation practices. Future work would also benefit from using analytical techniques like structural equation modeling with latent variables (SEMLV) to extend our empirical findings. We recommend conducting multi-level analyses incorporating adoption measures at community, county, state, and even regional levels, which will link individual adoption, increases in acreage, and time with community diffusion to account for the role that context plays in shaping practice adoption. Including more biophysical factors will be an intriguing extension. Future studies that investigate how environmental characteristics such as precipitation, temperature, soil moisture, and soil organic matter associate with cover crop use can inform human-nature interactions, and such models can also be examined using a multilevel approach.

Summary and Conclusions

We used data from 1,724 corn and soybean farms in Illinois, Indiana, Michigan, and Ohio to test three models that predicted three cover crop use measures, including single-year cover crop use on a specific field, single-year percent of acres planted to cover crops on a farm, and years of cover crop use. We specified an empirical model that included biophysical, operational, policy, social, and attitudinal factors, along with control variables to predict cover crop use at the field and farm levels.

The importance of perceived soil health benefits, knowledge, profits, no-till, and rotational diversity are confirmed in our study. Many policies and education programs have focused on increasing the perceived efficacy and knowledge of conservation practices. Findings from this study further highlight the potential of building a conservation practice system and utilizing the spill-over effects between practices. Farmers who use conservation practices in a diverse cash crop rotation system are more likely not only to try new practices but also to use the practice on a larger portion of their land and for more years. How to get the farmers to a point where their operating system is conducive to innovation and change could be a new direction for conservation policies and programs.

In comparison, factors like conservation programs, crop insurance, and sustainability goals have more specific targets such as increasing farmers, acres, or years of use. These factors need to join with other factors to achieve not only the desired number of farmers but also the number of acres and years. For example, participating in a conservation program may need to increase perceived soil health benefits and knowledge and lessen the relative importance of profit goals to be able to sustain and expand change. Incentive programs should incorporate educational outcomes. In addition, crop insurance, although not inhibiting farmers from using the practice at the field level, is negatively associated with years of use. Practitioners need to discern if that may be legacy effects of the deficiency in the earlier crop insurance programs or if there are more systematic changes needed to improve the compatibility between crop insurance and conservation. Although sustainability goals may not be enough to increase the number of adopters or the extent of adoption, it is still important in sustaining its use. People's values and goals are difficult to change but a slow transition of society's priorities and norms for agriculture is possible and may even be happening. The increased awareness of soil health is an example.

Promoting sustained use and sustainability farming goals is a contributor and part of the transition that is worth more attention.

Our results provide new insights into how to scale up cover crop use across farmers, time, and space. We suggest policies and educational programs that increase perceived efficacy and knowledge about cover crops, help with profits, and promote an operating system conducive to innovations and conservation are more likely to increase the number of farmers, acres, and years of cover crop use to achieve sustainability goals.

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References

Abdalla, M., A. Hastings, K. Cheng, Q. Yue, D. Chadwick, M. Espenberg, J. Truu, R. M. Rees, and P. Smith. 2019, August 1. A critical review of the impacts of cover crops on nitrogen leaching, net greenhouse gas balance and crop productivity. Blackwell Publishing Ltd.

Arbuckle, J. G., L. S. Prokopy, T. Haigh, J. Hobbs, T. Knoot, C. Knutson, A. Loy, A. S. Mase, J. McGuire, L. W. Morton, J. Tyndall, and M. Widhalm. 2013. Climate change beliefs, concerns, and attitudes toward adaptation and mitigation among farmers in the Midwestern United States. Climatic Change 117(4):943–950.

Arbuckle, J. G., and G. Roesch-McNally. 2015. Cover crop adoption in Iowa: The role of perceived practice characteristics. Journal of Soil and Water Conservation 70(6):418–429.

584 Basche, A. D., and G. E. Roesch-McNally. 2017. Research topics to scale up cover crop use: Reflections
585 from innovative Iowa farmers. Journal of Soil and Water Conservation 72(3):59A-63A.

586 Beetstra, M. A., R. S. Wilson, and M. Doidge. 2022. Conservation behavior over time: Examining a
587 Midwestern farmer sample. Land Use Policy 115 (April 1, 2022).

588 Burnett, E., R. S. Wilson, A. Heeren, and J. Martin. 2018. Farmer adoption of cover crops in the western
589 Lake Erie basin. Journal of Soil and Water Conservation 73(2):143–155.

590 Carlisle, L. 2016. Factors influencing farmer adoption of soil health practices in the United States: a
591 narrative review. Agroecology and Sustainable Food Systems 40(6):583–613.

592 Church, S. P., J. Lu, P. Ranjan, A. P. Reimer, and L. S. Prokopy. 2020. The role of systems thinking in
593 cover crop adoption: Implications for conservation communication. Land Use Policy 94 (May 1,
594 2020).

595 Connor, L., R. M. Rejesus, and M. Yasar. 2021. Crop insurance participation and cover crop use:
596 Evidence from Indiana county-level data. Applied Economic Perspectives and Policy (2021).

597 Cusser, S., C. Bahlai, S. M. Swinton, G. P. Robertson, and N. M. Haddad. 2020. Long-term research
598 avoids spurious and misleading trends in sustainability attributes of no-till. Global Change Biology
599 26(6):3715–3725.

600 Dillman, D. A., J. D. Smyth, and L. M. Christian. 2014. Internet, Phone, Mail, and Mixed-Mode Surveys:
601 The Tailored Design Method. 4th ed. Hoboken, NJ: John Wiley & Sons, Inc.

602 Dosskey, M., G. Wells, G. Bentrup, and D. Wallace. 2012. Enhancing ecosystem services: Designing for
603 multifunctionality. Journal of Soil and Water Conservation 67(2).

604 Dunn, M., J. D. Ulrich-Schad, L. S. Prokopy, R. L. Myers, C. R. Watts, and K. Scanlon. 2016.
605 Perceptions and use of cover crops among early adopters: Findings from a national survey. Journal
606 of Soil and Water Conservation 71(1):29–40.

607 Epanchin-Niell, R. S., D. B. Jackson-Smith, R. S. Wilson, M. Ashenfarb, A. A. Dayer, V. Hillis, G. D.
608 Iacona, E. M. Markowitz, S. T. Marquart-Pyatt, and T. Treakle. 2022, January 15. Private land
609 conservation decision-making: An integrative social science model. Academic Press.

610 Fleckenstein, M., A. Lythgoe, J. Lu, N. Thompson, O. Doering, S. Harden, J. M. Getson, and L. Prokopy.
611 2020. Crop insurance: A barrier to conservation adoption? Journal of Environmental Management
612 276 (December 15, 2020).

613 Guo, T., V. Campbell-Arvai, and B. J. Cardinale. 2021. Why does the public support or oppose
614 agricultural nutrient runoff regulations? The effects of political orientation, environmental
615 worldview, and policy specific beliefs. Journal of Environmental Management 279 (January 15,
616 2021).

617 Hewitt, J. E., S. F. Thrush, and C. Lundquist. 2017. Scale-Dependence in Ecological Systems. *In* eLS, 1–
618 7. Chichester: John Wiley & Sons, Ltd.

619 Houser, M., S. T. Marquart-Pyatt, R. C. H. Denny, A. Reimer, and D. Stuart. 2019. Farmers, information,
620 and nutrient management in the US Midwest. Journal of Soil and Water Conservation 74(3):269–
621 280.

622 Kuhfuss, L., R. Préget, S. Thoyer, N. Hanley, P. le Coent, and M. Désolé. 2016. Nudges, social norms,
623 and permanence in agri-environmental schemes. Land Economics 92(4):641–655.

624 Lee, S., and L. McCann. 2019. Adoption of Cover Crops by U.S. Soybean Producers. Journal of
625 Agricultural and Applied Economics 51(4):527–544.

626 Luther, Z. R., S. M. Swinton, and B. van Deynze. 2020. What drives voluntary adoption of farming
627 practices that can abate nutrient pollution? Journal of Soil and Water Conservation 75(5):640–650.

628 Michalak, A. M., E. J. Anderson, D. Beletsky, S. Boland, N. S. Bosch, T. B. Bridgeman, J. D. Chaffin, K.
629 Cho, R. Confesor, I. Daloglu, J. v. DePinto, M. A. Evans, G. L. Fahnenstiel, L. He, J. C. Ho, L.
630 Jenkins, T. H. Johengen, K. C. Kuo, E. LaPorte, X. Liu, M. R. McWilliams, M. R. Moore, D. J.
631 Posselt, R. P. Richards, D. Scavia, A. L. Steiner, E. Verhamme, D. M. Wright, and M. A. Zagorski.
632 2013. Record-setting algal bloom in Lake Erie caused by agricultural and meteorological trends
633 consistent with expected future conditions. Proceedings of the National Academy of Sciences of the
634 United States of America 110(16):6448–6452.

635 Pannell, D. J., and R. Claassen. 2020. The roles of adoption and behavior change in agricultural policy.
636 Applied Economic Perspectives and Policy 42(1):31–41.

637 Plastina, A., F. Liu, F. Miguez, and S. Carlson. 2018a. Cover crops use in Midwestern US agriculture:
638 Perceived benefits and net returns. Renewable Agriculture and Food Systems (February 1, 2018):1–
639 11.

640 Plastina, A., F. Liu, W. Sawadgo, F. Miguez, and S. Carlson. 2018b. Partial budgets for cover crops in
641 midwest row crop farming. Journal of the ASFMRA (2018):90–103.

642 Plastina, A., F. Liu, W. Sawadgo, F. E. Miguez, S. Carlson, and G. Marcillo. 2018c. Annual net returns to
643 cover crops in Iowa. Journal of Applied Farm Economics 2(2).

644 Prokopy, L. S., K. Floress, J. G. Arbuckle, S. P. Church, F. R. Eanes, Y. Gao, B. M. Gramig, P. Ranjan,
645 and A. S. Singh. 2019. Adoption of agricultural conservation practices in the United States:
646 Evidence from 35 years of quantitative literature. Journal of Soil and Water Conservation
647 74(5):520–534.

648 Prokopy, L. S., B. M. Gramig, A. Bower, S. P. Church, B. Ellison, P. W. Gassman, K. Genskow, D.
649 Gucker, S. G. Hallett, J. Hill, N. Hunt, K. A. Johnson, I. Kaplan, J. P. Kelleher, H. Kok, M. Komp,
650 P. Lammers, S. LaRose, M. Liebman, A. Margenot, D. Mulla, M. J. O'Donnell, A. W. Peimer, E.
651 Reaves, K. Salazar, C. Schelly, K. Schilling, S. Secchi, A. D. Spaulding, D. Swenson, A. W.
652 Thompson, and J. D. Ulrich-Schad. 2020. The urgency of transforming the Midwestern U.S.
653 landscape into more than corn and soybean. Agriculture and Human Values 37(3):537–539.

654 Reimer, A., J. E. Doll, T. J. Boring, and T. Zimnicki. 2021. Scaling up conservation agriculture: An
655 exploration of challenges and opportunities through a stakeholder engagement process. Journal of
656 Environmental Quality (2021).

657 Reimer, A. P., R. C. H. Denny, and D. Stuart. 2018. The Impact of Federal and State Conservation
658 Programs on Farmer Nitrogen Management. Environmental Management 62(4):694–708.

659 Reimer, A., A. Thompson, L. S. Prokopy, J. G. Arbuckle, K. Genskow, D. Jackson-Smith, G. Lynne, L.
660 McCann, L. W. Morton, and P. Nowak. 2014. People, place, behavior, and context: A research

agenda for expanding our understanding of what motivates farmers' conservation behaviors. Journal of Soil and Water Conservation 69(2).

Robertson, G. P., K. L. Gross, S. K. Hamilton, D. A. Landis, T. M. Schmidt, S. S. Snapp, and S. M. Swinton. 2014. Farming for ecosystem services: An ecological approach to production agriculture. American Institute of Biological Sciences.

Robertson, G. P., S. K. Hamilton, K. Paustian, and P. Smith. 2022. Land-based climate solutions for the United States. Global Change Biology 28(16):4912–4919.

Roesch-Mcnally, G. E., A. D. Basche, J. G. Arbuckle, J. C. Tyndall, F. E. Miguez, T. Bowman, and R. Clay. 2018. The trouble with cover crops: Farmers' experiences with overcoming barriers to adoption. Renewable Agriculture and Food Systems 33(4):322–333.

Sawadgo, W. P. M., W. Zhang, and A. Plastina. 2021. What drives landowners' conservation decisions? Evidence from Iowa. Journal of Soil and Water Conservation 76(3):211–221.

Sawadgo, W., and A. Plastina. 2021. Do cost-share programs increase cover crop use? Empirical evidence from Iowa. Renewable Agriculture and Food Systems (2021):1–9.

Schoolman, E. D., and J. G. Arbuckle. 2022. Cover crops and specialty crop agriculture: Exploring cover crop use among vegetable and fruit growers in Michigan and Ohio. Journal of Soil and Water Conservation 77(4):403–417.

Singer, J. W. ;, S. M. ; Nusser, and C. J. Alf. 2007. Are cover crops being used in the US corn belt? Journal of Soil and Water Conservation 62(5):353–358.

Snapp, S. S., S. M. Swinton, R. Labarta, D. Mutch, J. R. Black, R. Leep, J. Nyiraneza, and K. O'Neil. 2005. Evaluating cover crops for benefits, costs and performance within cropping system niches. Agronomy Journal 97 (2005):322–332.

Sneddon, J., G. Soutar, and T. Mazzarol. 2011. Modelling the faddish, fashionable and efficient diffusion of agricultural technologies: A case study of the diffusion of wool testing technology in Australia. Technological Forecasting and Social Change 78(3):468–480.

Thompson, N. M., C. J. Reeling, M. R. Fleckenstein, L. S. Prokopy, and S. D. Armstrong. 2021. Examining intensity of conservation practice adoption: Evidence from cover crop use on U.S. Midwest farms. Food Policy 101 (May 1, 2021).

Ulrich-Schad, J. D., S. Garciá De Jalón, N. Babin, A. Pape, and L. S. Prokopy. 2017. Measuring and understanding agricultural producers' adoption of nutrient best management practices. Journal of Soil and Water Conservation 72(5):506–518.

USDA-National Agricultural Statistics Service. 2019a. 2017 Census of Agriculture-Table 1. State Summary Highlights:2017.

USDA-National Agricultural Statistics Service. 2019b. 2017 Census of Agriculture-Table 41. Land Use Practices: 2017 and 2012.

USDA-National Agricultural Statistics Service. 2019c. 2017 Census of Agriculture-Table 45. Selected Operation and Producer Characteristics: 2017.

USDA-Natural Resources Conservation Service. 2022, January 10. USDA offers expanded conservation program opportunities to support climate smart agriculture in 2022.

Wallander, S., D. Smith, M. Bowman, and R. Claassen. 2021. Cover Crop Trends, Programs, and Practices in the United States.

Walpole, H. D., and R. S. Wilson. 2022. Why Do we Conserve?: Identifying Mechanisms in Agricultural Conservation Practice Adoption Decisions. Society and Natural Resources 35(3):340–352.

Weber, J. G., and D. M. Clay. 2013. Who does not respond to the agricultural resource management survey and does it matter? American Journal of Agricultural Economics 95(3):755–771.

Wojcik, D. J., M. C. Monroe, D. C. Adams, and R. R. Plate. 2014. Message in a bottleneck? Attitudes and perceptions of climate change in the cooperative extension service in the Southeastern United States. Journal of Human Sciences and Extension.

Yoder, L., M. Houser, A. Bruce, A. Sullivan, and J. Farmer. 2021. Are climate risks encouraging cover crop adoption among farmers in the southern Wabash River Basin? Land Use Policy 102 (March 1, 2021).

Table tiles

Table 1. Survey questions for independent variables

Table 2. Descriptive statistics for farm, field, and farmer characteristics

Table 3. Modeling results

Table 4. Predicted probability (Model 1 and 2) and predicted average years (Model 3) for consistent factors with all other variables held at their means or modes

Figure captions

Figure 2. Distribution of cover crop measures (a) single year field level cover crop use (b) single year farm level cover crop use (c) years of cover crop use