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Scaling up agricultural conservation: Predictors of cover crop use across time and space in the US 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 (*Zea mays* L.) and soybean (*Glycine max* [L.] Merr.) 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 percentage 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, and 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.

Key words: Corn Belt—farmer decision-making—practice adoption—scale

Scaling up agricultural conservation is critical for the transition of the US 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 (C), 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 US$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 USDA Natural Resources Conservation Service (NRCS) launched a new cover crop initiative in 11 states that provided US$38 million to help farmers implement the practice (USDA NRCS 2022). Many state-level programs also exist. For example, Ohio pays US$12 to US$40 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 ac [6.2 million ha]) is still markedly lower than the acreage planted to corn (*Zea mays* L.) and soybean (*Glycine max* [L.] Merr.) (174.9 million ac [70.8 million ha]), according to the 2017 Census of Agriculture administered by the USDA National Agricultural Statistics Service (USDA NASS 2019a, 2019c). It is also far lower than the total acres under no-till (104.5 million ac [42.3 million ha]), another conservation practice that reduces the disturbance of soil and improves soil health (USDA NASS 2019a; 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 US 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

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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 (2020) 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 necessary. While studies that use binary measures of cover crop adoption capture the factors that influence farmers to adopt, providing valuable information about how to scale up adoption by reaching more farmers, they fail to include analyses that inform us about scaling up across time and space. Here, we aim to address all three dimensions, and investigate whether the factors that previously have been shown to be influential on initial adoption of cover crops are also influential on the number of acres and number of years of use. The investigation is motivated by the concept that relationships and patterns apparent with one measurement strategy or at one scale may not manifest when viewed from other scales, and the profound impacts of considering scales in study design and analysis (Hewitt et al. 2017). Such an investigation requires the incorporation of novel levels of measurement to the practice adoption literature. The proportion of a farm's total acres planted to cover crops tells us about the spatial extent of adoption, referred to here as intensity (or extent). The number of years cover crops have been planted on a farm tells us about the continued use of the practice over time or its temporal extent, referred to as longevity. In the following sections, we first summarize factors that have been studied influencing cover crop use in general, then propose how models for adoption, intensity, and longevity of the use of cover crops may differ.

Factors Influencing Cover Crop Use. The adoption literature has identified a range of factors explaining cover crop use and other conservation practice adoption in general that includes psychological, social, policy, operational, biophysical, and demographic factors, suggesting multiple mechanisms (Carlisle 2016; Prokopy et al. 2019). Many empirical models are implicitly or explicitly guided by the proposition that farmer conservation behaviors are driven by interactions between attributes of the decision-maker, the decision context, and attributes of potential conservation behaviors (Epanchin-Niell et al. 2022).

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

In addition to farmers' thoughts and motivations, farm operational characteristics, policy, social context manifested as information exchange, and biophysical factors also play a role. Farms already managed with other conservation practices such as conservation tillage, extended crop rotation, and integrated with livestock production are more likely to use cover crops (Singer 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. (2007), Arbuckle and Roesch-McNally (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 plant 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 long-term 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 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.

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

For the biophysical characteristics of a field and a farm, the typology of a field relates to yet differs from the typology of a farm, which may affect the management of a single field and the whole farm differently. These factors have specific spatial and temporal boundaries. However, operational factors that form the decision context may consistently affect adoption, intensity, and longevity of use. For example, using no-till was associated with cover crop adoption (binary measure) (Lee and McCann 2019; Thompson et al. 2021) and intensity of implementation (Thompson et al. 2021). The number of crops a farm manages and having livestock was also found to be associated with different binary measures of adoption, such as cover crop use ever in the past (Singer et al. 2007; Lee and McCann 2019), on their farm in a single year (Arbuckle and Roesch-McNally 2015), and on soybean fields in a single year (Lee and McCann 2019).

Policy factors such as crop insurance and conservation programs also comprise important decision contexts. They may consistently affect adoption and intensity of use, but their effects on longevity will depend on when and where adoption is measured, as policy programs often have start dates, end dates, and modification dates for different regions. Supporting our expectation that policy factors affect adoption, intensity, and longevity of use differently, Connor et al. (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 percentage 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 US upper Midwest corn and soybean farms using three generalized linear models.

Materials and Methods

Study Context. The US 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 four 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 four states comprised more than 55 million ac of cropland (22.3 million ha), with 82.6% of that acreage planted to corn or soy. Specifically, 39.3% of total cropland acres across these four states were planted to corn, and 43.3% were planted to soy in 2017 (USDA NASS 2019b).

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 ac (40.5 ha), 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 ac (40.5 and 201.9 ha), and farmers operating 500 or more ac (202.3 or more ha). 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 multiwave survey-postcard format distributed to farmers from February to April of 2018. Potential participants received a prenotice postcard, followed by a mailing with a copy of the survey instrument, a cover letter, and a prepaid, 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).

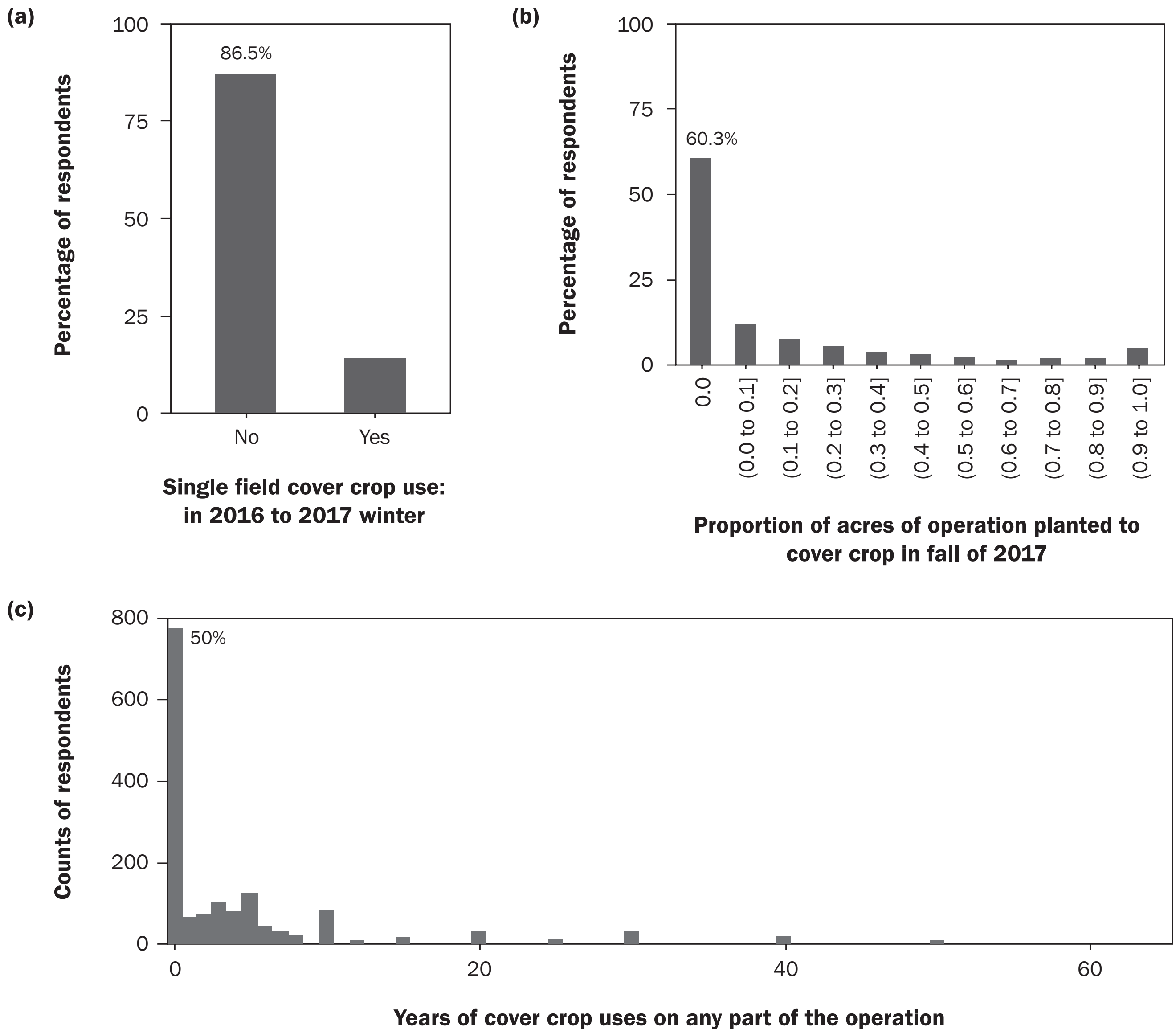
Measures. We designed the questionnaire by drawing on previous research and in consultation with agronomists, ecologists, and stakeholders related to the USDA Long-Term Agroecosystem Research (LTAR) network. In this analysis, we focused on cover crop use and pertinent farm, field, and farmer characteristics. 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 to 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.

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.

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 table S1). 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 (table S1). 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-till was used on the

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



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 overdispersed 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 data sets, each model passed the Hosmer-Lemeshaw tests (for binary and quasi-binomial regression insignificant chi-

Table 1
Survey questions for independent variables.

Topic	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 and 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 and 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, and veg crops; 3 = flowers, ornamentals, and 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

squared) or the likelihood test (for negative binomial model). Goodness-of-fit tests were conducted for individual imputation data sets. For each model, five data sets 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 and Discussion

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 NASS 2019b). 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 ac (279.2 ha). On average, each farm had 14% of their acreage planted to cover crops in the 2016 to 2017 winter, with 60% of farms having 0 ac 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 ac (40.9 ha). About 14% of the fields were planted to cover crops in the 2016 to 2017 winter. Sixteen percent of the fields were classified as highly erodible, and 33% were reported to be no-till. Most of the fields were reported to have a "somewhat sandy" soil texture (53%), which includes clay, clay loam, and loam soil types; only 2% were reported as being sandy.

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, and 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.

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

Discussion. We conducted analyses with data from 1,724 corn and soybean farms in Illinois, Indiana, Michigan, and Ohio on the use of cover crops at the field and farm levels, and over years. We accounted for broader contextual factors (e.g., biological conditions, economic factors, and existing farming systems), personal factors (e.g., attitudes, knowledge, and goal orientations), and farm and farmer characteristics as controls, moving toward a baseline adoption model. Although we expected to see models for adoption, intensity, and longevity of cover crop use mostly differ, we uncovered five factors having consistent effects across scales. These factors are perceived soil 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

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

Variable	Unit	Mean	sd	Min	Max
Percentage of fields planted to a cover crop in 2016 to 2017 winter	0/1	0.14	—	0	1
Proportion of acreage within a farm planted to cover crop in fall of 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 information from private sources	0/1	0.96	—	0	1
Received information 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 (y)	Number	32.58	14.24	1	71
Education: have degree more than high school	0/1	0.57	—	0	1
Field size (ac)	Number	100.72	104.55	5	3,015
Farm size (ac)	Number	690.05	654.84	100	7,063
Proportion of acres owned by the farmer	Number	0.63	0.35	0	1

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

Table 3
Modeling results.

Variable	Outcomes: Model 1: Adoption	Model 2: Intensity	Model 3: 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 (y)	0.006	−0.02***	0.004
Education: have degrees more than high school	0.22	0.20	−0.10
Field size (ac)	0.0004	—	—
Farm size (ac)	−0.00003	−0.00008	0.0003***
Proportion of acres owned by the farmer	0.06	0.85***	0.04
Valid *n*	1,721	1,666	1,529
McFadden R^2	0.24	0.42	0.24
Link	Binary	Quasi-binomial	Negative-binomial

*p-value < 0.05. **p-value < 0.01. ***p-value < 0.001.

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 was positively associated with cover crop adoption and extent in the study

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

Outcome variables	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

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

The effect of crop insurance also differed across outcome variables. Our results did not find a negative association between crop insurance and cover crop adoption (Model 1), consistent with Fleckenstein et al. (2020) and Thompson et al. (2021), nor between crop insurance and cover crop extent (Model 2), inconsistent with Connor et al. (2021). However, the observational units differed, with counties in Connor et al. (2021), while the observational unit in our study was a farm. Noticeably, farmers who currently use crop insurance have, on average, been using cover crops for fewer years. Federal crop insurance policies have only recently changed to allow all insured farms to plant cover crops, which could explain this finding. Interestingly, farmers' contact with public information sources, private information sources, or other farmers did not produce significant associations with cover crop use across scales. It could be that the binary variables of information use did not capture the content and weight of individual information sources on cover crop use or that information has an indirect rather than a direct effect (Walpole and Wilson 2022).

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

Limitations and Future Research. It is worth noting that although we sought to cover important categories of predictors, future research could extend our models to include other potentially important predictors, including, for example, precipitation, temperature, soil moisture, and risk perception. Additionally, due to the complexity of categorical outcomes, we were not able to fit the models simultaneously, which would have otherwise allowed us to see whether farmers' decisions about cover crop adoption were connected across different scales. Some farmer, field, and farm characteristics were simplified to binary variables to reduce 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 multilevel 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 percentage 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.

Supplemental Material

The supplementary material for this article is available in the online journal at https://doi.org/10.2489/jswc.2023.00084.

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