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CORRIGENDUM

Corrigendum: Satellite detection of cover crops and their effects on crop yield in the Midwestern United States (2018 *Environ. Res. Let.* 13 064033)

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Supplementary material for this article is available online

Corrigendum Abstract

The original raw dataset used to generate this work contained a number of duplicate entries—roughly 7% of the total farm fields. The substantive majority of these were from one large farm that had conducted their operations in a way that caused duplication as a side effect in our data generation process. Unfortunately, as the error was in the raw dataset, its correction required a re-run of the entire data pipeline, resulting in numerous small downstream changes. With respect to the most important numbers, the accuracy of the classifier went down slightly from 91.5% to 91.2% measured in absolute terms but increased from 0.68 to 0.74 measured by kappa. The trend in cover cropped acres grew slightly stronger, and the yield effects in maize and soybean moved from 0.65% to 0.71% and 0.35% to 0.29% respectively. None of the overall conclusions of the work have materially changed. Below, we provide all changes to the applicable sections of the original manuscript in bold underscore (or strikethrough) where applicable, in addition to modified versions of the corresponding figures and supplementary materials.

Abstract

The practice of planting winter cover crops has seen renewed interest as a solution to environmental issues with the modern maize- and soybean-dominated row crop production system of the US Midwest. We examine whether cover cropping patterns can be assessed at scale using publicly available satellite data, creating a classifier with 91.2% accuracy (0.74 kappa). We then use this classifier to examine spatial and temporal trends in cover crop occurrence on maize and soybean fields in the Midwest since 2008, finding that despite increased talk about and funding for cover crops as well as a more than doubling of cover crop acres planted from 2008–2016, increases in winter vegetation have been more modest. Finally, we combine cover cropping with satellite-predicted yields, finding that cover crops are associated with low relative maize and soybean production and poor soil quality, consistent with farmers adopting the practice on fields most in need of purported cover crop benefits. When controlling for invariant soil quality using a panel regression model, we find modest benefits of cover cropping, with average yield increases of 0.71% for maize and 0.29% for soybean. Given these slight impacts on yields, greater incentives or reduced costs of implementation are needed to increase adoption of this practice for the majority of maize and soybean acres in the US.

Methods

Data processing

Raw data on cover cropping status by field and year from 24 different farm operators and/or landowners or agencies across eight states were acquired for the purposes of the study. While cash crop production years from 2007– 2018 were represented, 82% of the 2312 total field-years came from the penultimate three years of the interval.

…

Once the final imagery was compiled, pixels for cover-cropped and non-cover-cropped field areas were sampled for each image. In order to avoid the potential for mixed pixels across classes, sampled pixels came only

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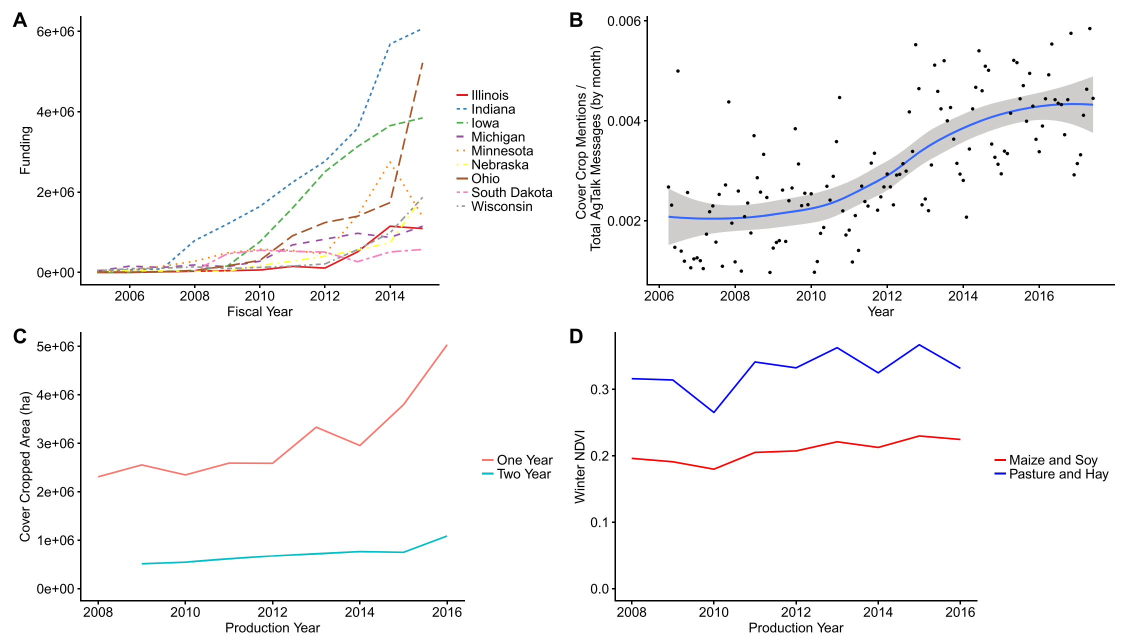

Figure 1.

from areas greater than 30 meters (one Landsat pixel) from a field boundary. Data from states bordering study area (e.g. Missouri and Pennsylvania) and 2018 were dropped at this step as well. 63 443 hectare-years of data (705 082 pixels) survived the buffer.

…

Data from 2035 unique field-years survived all of these filters.

Results

Classification

The classifier built for determining cover crop presence/nonpresence had an out-of-sample accuracy of 91.2%. Given the high prevalence of non-cover cropped fields, a more appropriate measure of performance, Cohen's kappa, registered (0.74 — well above the middle of the interval of 'substantial agreement' given by [47]. This compares favorably to the EWG [3] work that reported an accuracy of 72% with no kappa released. Variable importance plots for the identically parameterized classifier built using the R programming language [41] ranked the number of GDDs from the beginning of the off-season to the image date of the maximum NDVI image as the most important variable based on the mean decrease in Gini coefficient criterion.

Trends in cover cropping over time

…

Running the classifier across imagery from the 2008–2016 crop production years resulted in the pattern shown in figure 1(*c*). Here, the increase in cover cropping is apparent, with the lowest amount of cover crop area in 2008 at approximately 2.3 million ha, or 4.3% of the total acres planted to maize and soybean. The highest number of cover crop acres was in 2016 with 5.0 million planted to cover crops, or roughly 8.8% of the maize and soybean area. The trend in cover crop plantings over this nine-year period is significant at $p < 0.01$. Concern with multiple-year adoption of the practice led to a similar analysis for pixels in which at least two continuous years are cover cropped, showing a similar pattern with an increase from 0.51 to 1.09 million hectares in that category, or 1.0%–1.9% of cropped area (trend significant at $p < 0.01$).

…

Differences between cover cropped and non-cover-cropped fields

Using a linear model with controls for weather and soil quality and a time trend, cover cropped areas were associated with 0.18 Mg ha^{-1} lower yields for maize and 0.05 Mg ha^{-1} lower yields for soybean overall relative to conventional fields in the eight states for maize and three for soybean where SCYM-generated yields were available. Results of similar models built for each individual year are shown in panel A of figure 3. For maize, the largest yield differences were seen for the crops harvested in 2013 and 2015 with yields relatively lower by as much as 0.35 Mg ha^{-1}. For soybean, cover crop yields were relatively lowest in 2014 and 2009 with 0.14 and 0.11 Mg ha^{-1} differences observed. The gap between cover cropped and conventional yields increased with year for maize (significant at $p < 0.05$), but not for soybean.

Cover cropping was also associated with poorer quality soils, as seen in panel B. Pixels in the lowest decile for soil quality (as measured by the NCCPI) were 37% and 71% more likely than those at the median to be cover cropped for maize and soybean respectively. Pixels in the

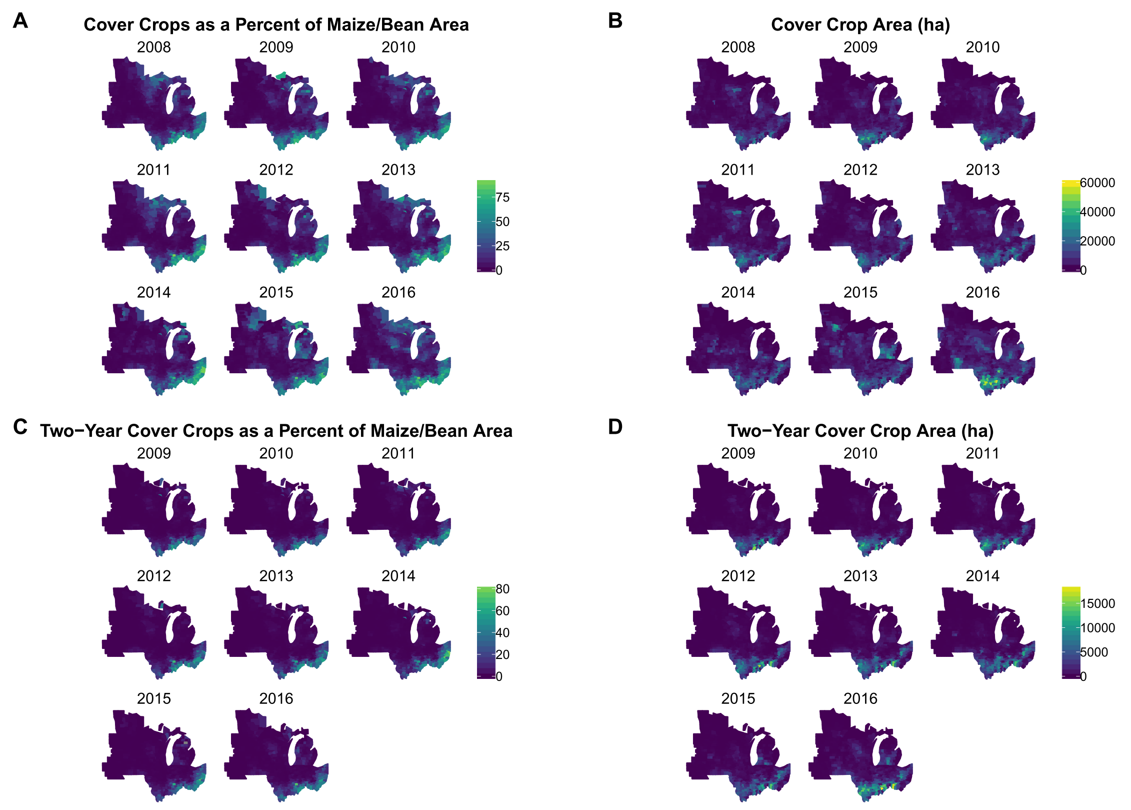

Figure 2.

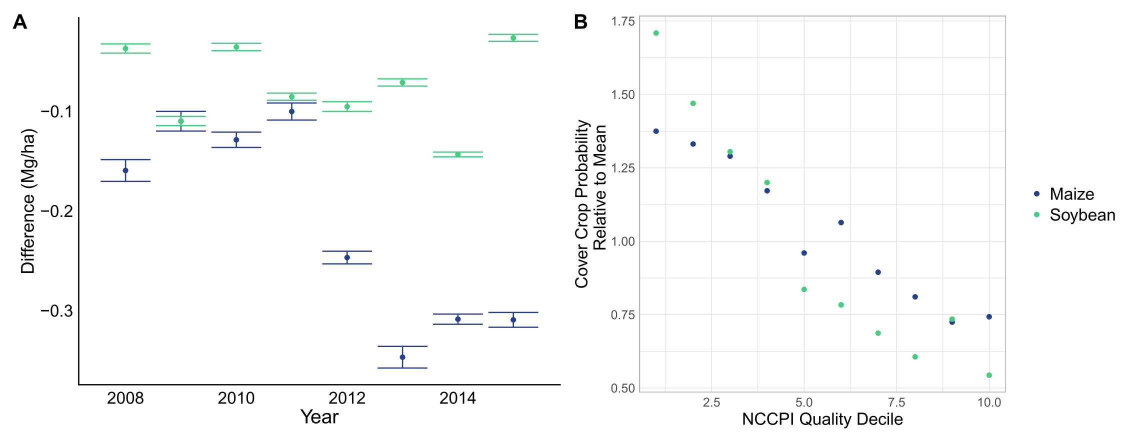

Figure 3.

highest decile of soil quality were 26% and 46% less likely than the median maize and soybean pixel to be cover cropped. This is despite the fact that soil quality was not included in the classifier used to determine presence/non-presence of cover crops. The pattern illustrated here even carries over into states with high general soil quality (e.g. Iowa).

Effects of cover cropping on yield by years cover cropped

While NCCPI serves as the best currently available nationwide soil quality index, it cannot account for soil properties such as compaction or nutrient depletion which vary at a scale far below what is mapped in SSURGO [49]. The index also cannot account for farmer practices which are likely to vary at the field or subfield level. The results of the panel regression created to eliminate the effects of such latent variables are shown in figure 4. Overall, this model showed a 0.71% increase for maize yields and a 0.29% increase for soybean yields in areas that used cover crops for at least a single year.

The model used here also allowed for the examination of trends over space, though not over time. Panel A of figure 4 shows that on maize fields, cover crops were

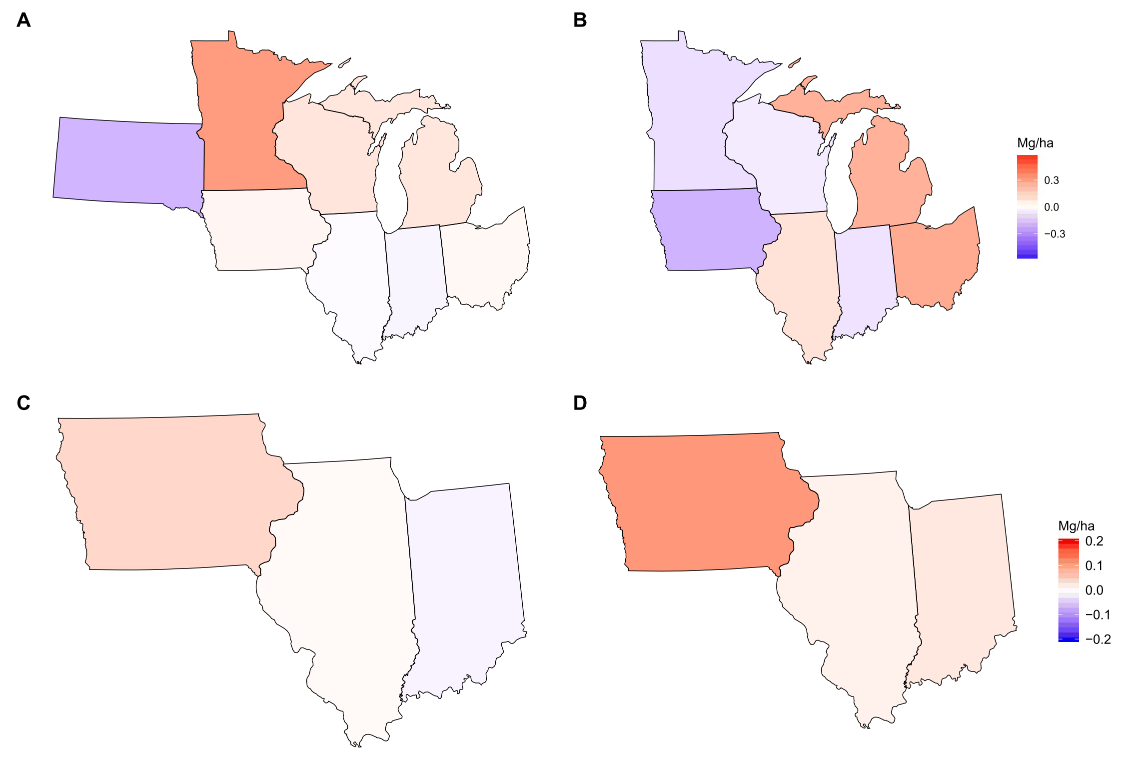

Figure 4.

most beneficial in Minnesota, Wisconsin and Michigan where benefits were 0.31, 0.08, and 0.08 Mg ha^{-1} respectively and least beneficial in Indiana and South Dakota with 0.03 and 0.19 Mg ha^{-1} decreases in yields with cover cropping. As shown in panel C, for soybean, benefits or losses were small regardless of state ranging from a loss of 0.01 Mg ha^{-1} in Indiana to a gain of 0.04 Mg ha^{-1} in Iowa.

Panels B and D of the figure show model outcomes comparing areas that had been cover cropped for at least three continuous years to areas not cover cropped. Here Michigan and Ohio show some of the largest benefits for maize, as illustrated in panel B; however, Indiana, Wisconsin, Iowa and Minnesota show yield decreases with long-term cover cropping (South Dakota was excluded here as less than 25 ha of maize area had followed the practice for three or more years in the dataset). For soybean, benefits increase with three years of cover cropping in Indiana, Illinois and Iowa with 0.03, 0.08 and 0.11 Mg ha^{-1} yield increases over effects seen with one year of cover cropping. In this figure in general, soybean yield effects are only shown in three states, reflecting the limited spatial extent of SCYM-generated yields for that crop.

Discussion

…

The real test of the effects of cover cropping on yields is whether cover cropped years of the same exact areas have higher yields than non-cover cropped years, controlling for weather. Here, cover crops show modest benefits of 0.71% and 0.29% for maize and soybean.

These benefits are comparable to [52] which found a 1.3% increase in maize yields, however, they are lower than the 3.8% soybean yield benefit reported. These numbers, however, were from a self-reported survey of growers following the practice so respondents may be vulnerable to a choice supportive bias [53] of cover crop adopters.

Cover cropping for multiple years does not appear to add a clear direction to the effects of the practice for maize. Two of the four states that benefit most with one year of cover cropping are also in the top four that benefit the most with three years, and large losses from cover cropping become apparent in other areas, potentially due to imperfect controls. However, for soybean, longer periods of cover crop adoption did appear to increase benefits. Overall, the data one both one- and three-year yield effects on maize and soybean appear to indicate a lack of generalized economically large yield benefits to cover crops in the Midwest.

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LETTER

Satellite detection of cover crops and their effects on crop yield in the Midwestern United States

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Supplementary material for this article is available online

Abstract

The practice of planting winter cover crops has seen renewed interest as a solution to environmental issues with the modern maize- and soybean-dominated row crop production system of the US Midwest. We examine whether cover cropping patterns can be assessed at scale using publicly available satellite data, creating a classifier with 91.5% accuracy (.68 kappa). We then use this classifier to examine spatial and temporal trends in cover crop occurrence on maize and soybean fields in the Midwest since 2008, finding that despite increased talk about and funding for cover crops as well as a 94% increase in cover crop acres planted from 2008–2016, increases in winter vegetation have been more modest. Finally, we combine cover cropping with satellite-predicted yields, finding that cover crops are associated with low relative maize and soybean production and poor soil quality, consistent with farmers adopting the practice on fields most in need of purported cover crop benefits. When controlling for invariant soil quality using a panel regression model, we find modest benefits of cover cropping, with average yield increases of 0.65% for maize and 0.35% for soybean. Given these slight impacts on yields, greater incentives or reduced costs of implementation are needed to increase adoption of this practice for the majority of maize and soybean acres in the US.

Introduction

Cover crops are nothing new to the American farm, with experiments growing 'other plants' between one year's maize harvest and the next year's maize planting dating back to at least the 1890s [1]. More modern interest in the practice, however, stems from farmers who wish to alleviate soil compaction, reduce soil erosion and reduce soil nitrogen loss [2], and has been accompanied by a large increase in funding available for farmers to adopt cover crops [3]. In reaction to this increased demand, new cover crop varieties and blends have been brought to market [4] and new equipment has been devised to lower costs associated with cover crop adoption [5].

Recent estimates indicate that these innovations and newly deployed funds could be inducing cover crop use. As of 2006, only 18% of farmers in a survey covering Illinois, Indiana, Iowa and Minnesota had used cover crops, and those farmers had only planted them on only 6% of their land the previous year, implying an overall adoption rate of a little over 1% [6]. By 2012, the US. Census of Agriculture found 0.68 million ha of cover crops planted in those same states, implying an overall adoption rate of 2.1% using planted acres [7, 8]. For just Illinois, Indiana and Iowa, the implied adoption rate in that survey was around 2.3% for 2012, but by 2015 the Environmental Working Group found an adoption rate of 3.4% [3]. It should be noted, however, that inconsistent measurement methodologies between these surveys could contribute to or cause the apparent trends.

Regardless, cover cropping remains a relatively rare practice, and there are major agronomic and operational challenges associated with it. These include getting the cover crop established, dealing with the increased time and labor requirements of running an operation that includes cover cropping, and figuring

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out what species might be the most beneficial in a given area [2]. There may also be allelopathic effects of some cover crop species such as cereal rye on cash crops such as maize [9, 10]. In addition to agronomic and operational challenges, economic challenges related to cover cropping include cost, a cover crop budget might run as high as 136 dollars per hectare [11], as well as structural factors (e.g. lack of use for biomass created by a cover crop due to absence of livestock on the farm [12]). Thus, even if yields are comparable, economic returns for cover crop adopters can be harmed [13]. These challenges, combined with recent negative returns for maize and soybean farming operations [14] have highlighted the critical importance of quantifying any potential economic returns to cover crop adoption.

The typical method for assessing these returns has been through field trials. A metastudy of such trials by Tonitto *et al* (2006) [15] found a roughly equal distribution of slightly positive and slightly negative yields for non-leguminous cover crops while a separate metastudy by Miguez and Bolero (2005) found a distribution of yields with more negative skew [16]. Similarly, more recent trials by the Practical Farmers of Iowa found decreases of as much as 1.4 Mg ha^{-1} and increases of as much as 0.5 Mg ha^{-1} for cover crops on maize and −0.2–0.5 Mg ha^{-1} yield differences for cover crops on soybean [17]. Adding insight for potential mechanisms, Reese *et al* (2014) [18] found that cover crops reduced yields when moisture was scarce in the production cycle following their use, but had no effect otherwise. While these sorts of studies have an advantage that they allow for strong claims of causality, they are subject to limited applicability based on site-specific weather, soil qualities, and management practices where they took place.

As an alternative, the combination of satellite-based classifiers and satellite-based yield assessments offers the potential to assess the yield effects of cover crops at scale. Such assessments have been applied to limited areas and timescales, with Hively *et al* (2015) [19] running one such assesment for Southeastern Pennsylvania for 2010–2013 and the Environmental Working Group producing one for Iowa, Illinois and Indiana for 2015 [3]. These assessments have the potential for wider applicability and insight into patterns at larger spatial and temporal scales but cannot definitively prove causality. However, even if clams at causality are limited, scalable mapping of cover crops alone can show whether funding to programs like the Natural Resources Conservation Service's Environmental Quality Incentives Program (NRCS EQIP) are having an effect on adoption as well as show the way for scalable verification of cover crop establishment.

In this study, we set out to use such a classifier to examine not only trends and patterns in cover crop adoption but also yield effects of cover crop adoption over time, with the hope that the information provided can be used to more thoughtfully construct government, nonprofit, and private sector programs in relation to the practice.

Methods

Data processing

Raw data on cover cropping status by field and year from 24 different farm operators and/or landowners or agencies across eight states were acquired for the purposes of the study. While cash crop production years from 2007–2017 were represented, 83% of the 2491 total field-years came from the last three years of the interval. In addition, Landsat 5, 7 and 8 imagery available through the Google Earth Engine (GEE) platform [20] served as the primary source of remotely sensed data for the analysis. These data were corrected to surface reflectance and georeferenced by the United States Geological Survey [21].

For each production year, imagery for the interval from the previous year's 'off-season' was composited for the study region—Ohio, Michigan, Wisconsin, Indiana, Illinois, Iowa, Minnesota and the portions of South Dakota and Nebraska where cover crop termination at planting is an accepted practice by the USDA's Risk Management Agency (USDA RMA) [22]. The off-season was defined as the midpoint of the date range of the 90th percentile category for a climatologically late, hard (−2.2 °C) freeze for each state, as made available by the Midwestern Regional Climate Center's Vegetative Impact Program [23] to the first day of planting allowed for maize by USDA RMA [24]. An analysis of the effects of having the interval vary can be found in figure S1 of the supplementary materials available at stacks.iop.org/ERL/13/064033/mmedia.

In addition Landsat data, MODIS data were used to get average values of vegetative indices for the dates of the Landsat imagery. Finally, weather data were compiled for each image using the Daymet gridded daily weather dataset [25], the vapor pressure data of which were transformed to vapor pressure deficit (VPD) [26–27] and added as bands to the composite image.

This resulted in a set of ten images with 23 bands. The subset of bands used for classification is outlined in table 1. Here it should be noted that despite the slight difference in Landsat 5/7 and 8 sensor platforms, Li *et al* (2013) [28] found that they can be used as complementary data for similar purposes and Flood (2014) [29] found small mean absolute differences between Normalized Difference Vegetation Index (NDVI) measurements across the sensors. Growing degree days (GDD) for the final band were based on a 0 C base temperature given its appropriateness for many cover crop varieties (e.g. wheat, rye, oats) [30, 31].

Once the final imagery was compiled, pixels for cover-cropped and non-cover-cropped field areas were sampled for each image. In order to avoid the potential for mixed pixels across classes, sampled pixels came only from areas greater than 30 meters (one Landsat

Table 1. Bands used in cover crop classifier.

Band	Math Applied
Green	Median
NIR	Median
SWIR1	Median
NDVI	Median, Minimum, Maximum
Number of Images	Count
Landsat-MODIS NDVI difference	Median-Mean, Minimum-Mean, Maximum-Mean
GDD	Sum from 11/1 to Median, Minimum and Maximum NDVI image dates

pixel) from a field boundary. Data from states bordering study area (e.g. Missouri and Pennsylvania) were dropped at this step as well. 71 524 hectare-years of data (794 890 pixels) survived the buffer.

To avoid issues with spatial autocorrelation, the pixels were grouped by fields and split into training and test samples. Pixels from 80% of the fields were used as training and pixels from the remaining 20% of fields were used to test the classification. Random forest was chosen as the classification method given examples of high performance on imbalanced training datasets [32, 33]. Parameters were set as 128 trees given [34], and 4 variables per tree (rounding the square root of predictors), and a minimum of 5 pixels per node (on the grounds that no decision should be made on less than a ~.45 hectare, or roughly one-acre, basis). This classifier was then used to categorize a masked version of the original images' pixels as cover cropped or not. The mask here was based on which pixels were classified as maize or soybean pixels in the following year's cropland data layer (CDL) [35] so as to avoid potential contamination issues with winter wheat and winter rye, which may have a very similar spectral appearance. This eliminated years without a national CDL at the time of the analysis (i.e. 2017 and 2007). Data from 2247 unique field-years survived all of these filters.

The accuracy of the classifier was gauged according to the number of correct classifications on the test dataset/total number of pixels in the dataset in addition to Cohen's kappa (k), given in equation 1:

$$k = 1 - \left(1 - p_o\right) / \left(1 - p_c\right) \tag{1}$$

where p_o is the accuracy and p_c is the probability of chance agreement.

In an effort to find corroboration of potential patterns seen in the classifier, we turned to two outside datasets. The first was a set of cover crop spending data obtained by the Environmental Working Group from the US. NRCS EQIP program under the Freedom of Information Act [36]. This dataset provided information for individual cover crop contracts that could be aggregated by state and year to look at funding trends for the practice. We also obtained over five million posts from the farm-focused online discussion forum AgTalk [37] cited as a promising information and communication technology by [38]. Using these data, we analyzed the number of cover crop mentions as a proportion of all posts to see if trends in following the practice might be corroborated there as well, similar to how mentions on the social network Twitter might help predict multiparty election results [39] or movie box office revenues [40].

In order to examine the influence of cover crops on yields, we sampled 7500 pixels classified as cover cropped and 7500 pixels classified as non-cover cropped by county (fewer than 7500 cover cropped pixels were used in counties with fewer than that many pixels classified as cover crop). Linear regression in the R programming language [41] was used to examine correlations between yield and a set of weather and soil covariates, in addition to cover cropping. The yield estimates for this analysis were obtained from analyses based on Landsat using the scalable crop yield mapper (SCYM) for maize and soybean [42]. The original implementation of SCYM covered Iowa, Illinois, and Indiana, and thus our soybean yield analysis is limited to those states. For maize, a more recent version [43] was used that contained yield estimates for all states in the study area except Nebraska. The accuracy of SCYM has been assessed at both field and county level, as reported elsewhere [43–46]. Overall, SCYM captures a significant fraction of variability in yields across fields, and any errors for grain yield estimates should be unrelated to cover crop status as no images from the off-season are used in yield estimation.

Specifically, we estimated the following regression:

$$y_i = U_i\alpha + T_i\beta + V_i\delta + W + X\tau + \varepsilon \tag{2}$$

where y is yield in year i, U is cover cropping status as a factor, T is the year, V is a set of weather covariates, W is National Commodity Crop Productivity Index Version 2 (NCCPI) for maize and soybean as derived from the SSURGO data, X is water holding capacity, derived from the same and ε is the error term. The (related) model examining patterns by year simply dropped the year term. Yield differences between cover cropped and conventional fields can therefore be thought of as the difference in predicted yields between cover cropped and conventional fields, taking all other covariates into account.

Although equation [2] attempts to control for weather and soil differences between fields with and without cover crops, we recognize that many aspects of soil in particular are hard to capture with existing datasets. Therefore, we also considered a panel regression model to examine how cover crops influenced yields in the same area(s) over time:

$$y_i = U_i\alpha + T_i\beta + V_i\delta + F + \varepsilon \tag{3}$$

where y, U T and V are as above and F is a pixel-level fixed effect.

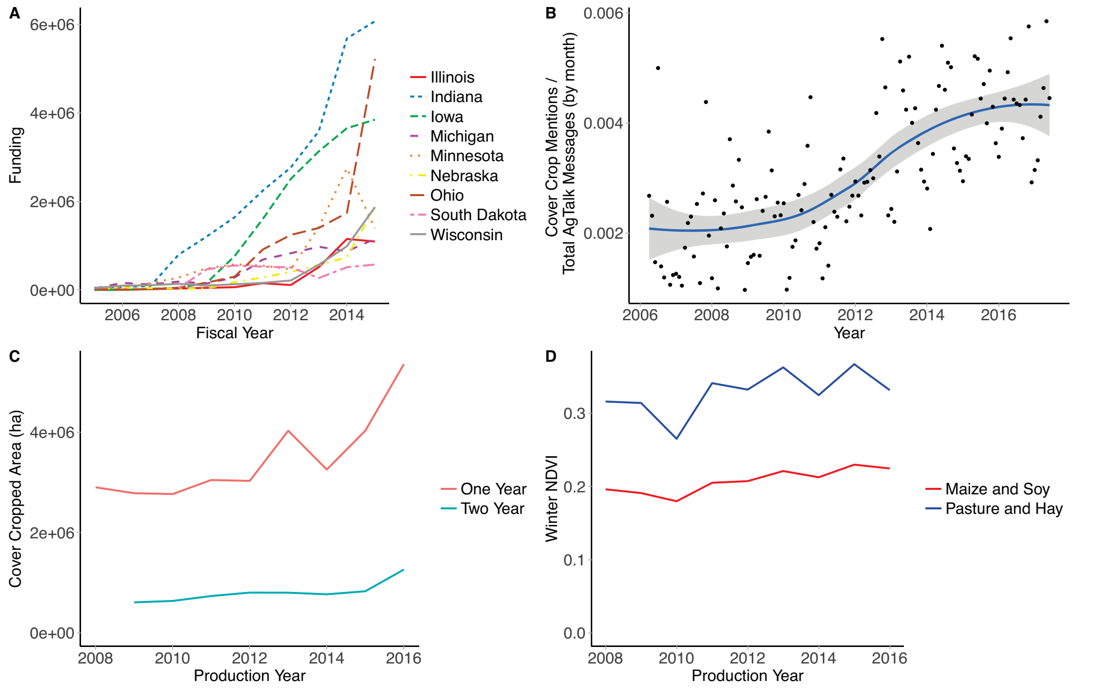

Figure 1. Trends in cover crop funding from EQIP data provided by Rundquist and Carlson (*a*), cover crop mentions from AgTalk (*b*), satellite-derived plantings (*c*) and resultant winter NDVI (*d*) over time.

Results

Classification

The classifier built for determining cover crop presence/nonpresence had an out-of-sample accuracy of 91.5%. Given the high prevalence of non-cover-cropped fields, a more appropriate measure of performance, Cohen's kappa, registered 0.68—slightly below the middle of the interval of 'substantial agreement' given by [47]. This compares favorably to the EWG [3] work that reported an accuracy of 72% with no kappa released. Variable importance plots for the identically parameterized classifier built using the R programming language [41] ranked maximum NDVI and the number of GDDs from the beginning of the off-season to the image date of the maximum NDVI image as the most important variables based on the mean decrease in Gini coefficient criterion.

Trends in cover cropping over time

Echoing an analysis done by the Environmental Working Group [3] as well as using related raw data [36] to look at patterns across the entire study area, figure 1(*a*) shows that funding for cover crops has increased drastically during much of the study period. This analysis is broadly consistent with a Government Accountability Office report citing a 273% increase in EQIP cover crop funding from fiscal year 2009 to fiscal year 2014 [48]. Here, the largest increases in absolute dollar terms have come in Indiana and Ohio, where funding has grown from a nominal amount to 6.1 and 5.2 million dollars respectively. Funding in Iowa also increased from a nominal amount to 3.8 million dollars. While funding increases were substantial in all states other than South Dakota in the dataset, amounts remained below 2 million dollars in those states.

Likewise, mentions of cover crops have also increased on the farm-focused online discussion forum, AgTalk. As seen in figure 1(*b*), posts mentioning cover crops increased in their relative frequency from roughly two per thousand to over four per thousand over the study period.

Running the classifier across imagery from the 2008–2016 crop production years resulted in the pattern shown in figure 1(*c*). Here, the increase in cover cropping is apparent, with the lowest amount of cover crop area in 2010 at approximately 2.8 million ha, or 5.1% of the total acres planted to maize and soybean. 2008 was near this nadir as well with 2.9 million ha of cover crops. The highest number of cover crop acres was in 2016 with 5.4 million planted to cover crops, or roughly 9.4% of the maize and soybean area. The trend in cover crop plantings over this nine-year period is significant at $p < .01$. Concern with multiple-year adoption of the practice led to a similar analysis for pixels in which at least two continuous years are cover cropped, showing a similar pattern with an increase from 0.61 to 1.26 million hectares in that category, or 1.2%–2.1% of cropped area (trend significant at $p < .05$).

Along with this increase in cover crop plantings, there has also been an increase in winter NDVI of maize and soybean fields as shown in figure 1(*d*). This trend is also significant ($p < .01$) and bears similarity

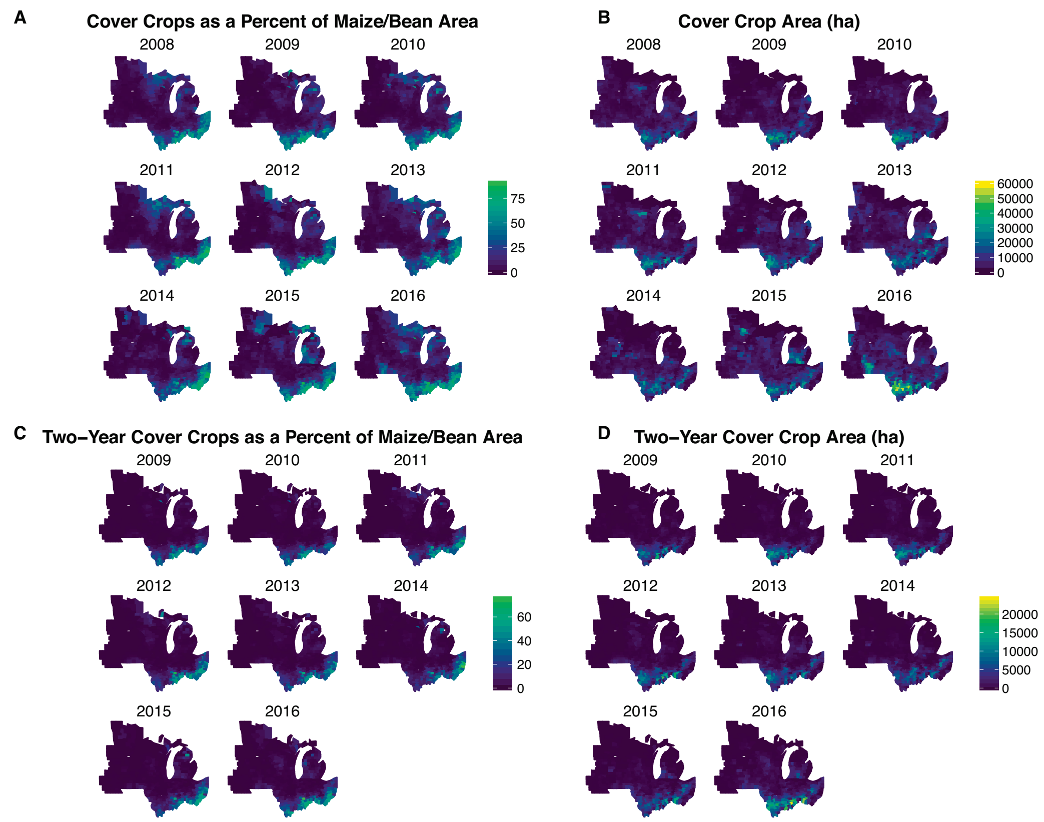

Figure 2. Satellite-classified cover crop plantings mapped by year. Single-year plantings as a percent of maize and soybean area (*a*) and raw area (*b*). The same metrics as the top two panels, but for two-year plantings (*c*) and (*d*).

to the work of Hively *et al* (2015) who found distinctly increasing vegetative groundcover trends in Southeastern Pennsylvania. Given the additional Hively *et al* (2015) finding that post-maize cover crops with medium and high biomass have a similar NDVI to hay, we compared this trend to that in the hay and pasture landcover classes. Based on that standard, a large gap remains. Indeed, the size of the gap between the pasture and hay and maize and soybean wintertime NDVI values shows no significant decrease over the study period.

Trends in cover cropping over space

As shown in figure 2, summing the satellite-predicted cover crop acres by county shows Southern Indiana, Southern Illinois and Southern and Eastern Ohio as hotspots for cover cropping activity with Central to Western Wisconsin and Central to Western Michigan serving as secondary hotspots in northern areas and Western Iowa having relatively high adoption in some years in absolute but not percentage terms. Broadly, the areas of adoption and non-adoption are similar to the single-year maps produced by USDA ERS (2012) and EWG [3]. However, key differences with respect to those maps are the higher numbers reported here especially in Western Iowa and Southern Illinois and lower numbers in Central Minnesota and Michigan.

Given the concern about consistent adoption in the absence of subsidy of as described by [3], we also define cover cropping as an area having adopted the practice for two consecutive years and map this in panels C and D above. The analysis presented in these panels should be less vulnerable to idiosyncratic errors for any single year in the classifier. Again, areas of Southern Illinois, Indiana and Ohio are highlighted. Here, however the stark difference in adoption between those areas and northern areas is readily apparent. This large difference in multi-year adoption versus single-year adoption in northern areas may be driven by rotation effects, as the shorter growing season only allows for cover cropping behind early harvested crops.

Differences between cover cropped and non-cover-cropped fields

Using a linear model with controls for weather and soil quality and a time trend, cover cropped areas were associated with 0.19 Mg ha^{-1} lower yields for maize and 0.04 Mg ha^{-1} lower yields for soybean overall relative to conventional fields in the eight states for maize and three for soybean where SCYM-generated yields were available. Results of similar models built for each individual year are shown in panel A of figure 3. For maize, the largest yield differences were seen for the crops harvested in 2014 and 2015 with yields relatively lower by as much as 0.33 Mg ha^{-1}. For soybean, cover crop yields were relatively lowest in 2014 and 2009 with 0.13 and 0.11 Mg ha^{-1} differences observed. The gap between cover cropped and conventional

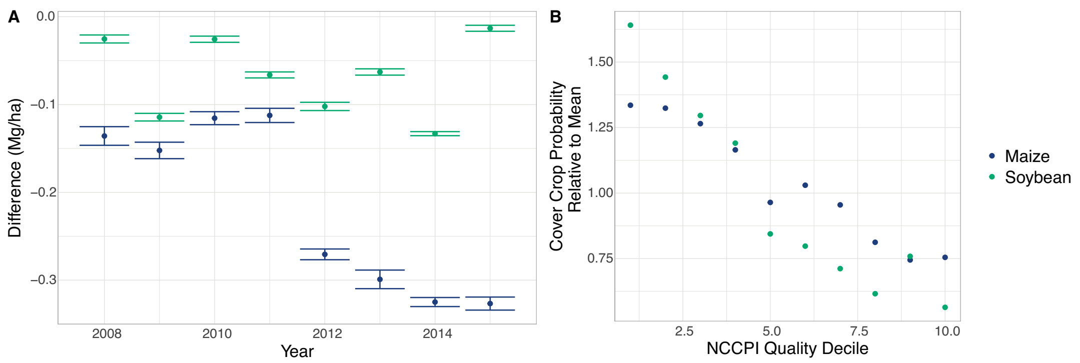

Figure 3. Yield difference for cover cropped versus conventional maize and soybean fields (*a*) relative probabilities of cover cropping by soil quality decile (*b*).

yields increased with year for maize (significant at $p < .01$), but not for soybean.

Cover cropping was also associated with poorer quality soils, as seen in panel B. Pixels in the lowest decile for soil quality (as measured by the NCCPI) were 34% and 64% more likely than those at the median to be cover cropped for maize and soybean respectively. Pixels in the highest decile of soil quality were 25% and 44% less likely than the median maize and soybean pixel to be cover cropped. This is despite the fact that soil quality was not included in the classifier used to determine presence/non-presence of cover crops. The pattern illustrated here even carries over into states with high general soil quality (e.g. Iowa).

Effects of cover cropping on yield by years cover cropped

While NCCPI serves as the best currently available nationwide soil quality index, it cannot account for soil properties such as compaction or nutrient depletion which vary at a scale far below what is mapped in SSURGO [49]. The index also cannot account for farmer practices which are likely to vary at the field or subfield level. The results of the panel regression created to eliminate the effects of such latent variables are shown in figure 4. Overall, this model showed a 0.65% increase for maize yields and a 0.35% increase for soybean yields in areas that used cover crops for at least a single year.

The model used here also allowed for the examination of trends over space, though not over time. Panel A of figure 4 shows that on maize fields, cover crops were most beneficial in Minnesota, Wisconsin and Ohio where benefits were 0.24, 0.07 and 0.05 Mg ha^{-1} respectively and least beneficial in Illinois and South Dakota with 0.004 and 0.33 Mg ha^{-1} decreases in yields with cover cropping. As shown in panel C, for soybean, benefits or losses were small regardless of state ranging from a loss of 0.003 Mg ha^{-1} in Indiana to a gain of 0.037 Mg ha^{-1} in Iowa.

Panels B and D of the figure show model outcomes comparing areas that had been cover cropped for at least three continuous years to areas not cover cropped. Here Michigan and Ohio show some of the largest benefits for maize, as illustrated in panel B; however, Indiana, Iowa and Minnesota show yield decreases with long-term cover cropping (South Dakota was excluded here as only 20 ha of maize area had followed the practice for three or more years in the dataset). For soybean, benefits increase with three years of cover cropping in Indiana and Iowa with .02 to .06 Mg ha^{-1} yield increases over effects seen with one year of cover cropping and are nearly unchanged in Illinois. In this figure in general, soybean yield effects are only shown in three states, reflecting the limited spatial extent of SCYM-generated yields for that crop.

Discussion

New tools for processing large swaths of satellite imagery in bulk have helped overcome the limitations of previous imagery-limited approaches [19] and have created the opportunity to map cover crops reliably at the region scale. The approach taken here shows that while discussion of, funding for, and planting of cover crops have all increased significantly over the past decade, the practice is still only used on a small minority of maize and soybean fields in the heart of the Midwest.

Often, cover crops are put forward to farmers as a way of improving soil productivity [50] and 66% of growers agree or strongly agree that cover crops can have that effect [51]. Thus, it is perhaps unsurprising that patterns in cover crop planting show that they are more likely to be used in areas with poor soils than in areas with good soils. While soil quality can be partly observed at the 30-meter scale of analysis used here, some elements of it cannot. Thus, it is also perhaps unsurprising that even with weather and soil controls, cover cropping is associated with poorer maize and soybean yields relative to conventional practice.

The real test of the effects of cover cropping on yields is whether cover cropped years of the same exact areas have higher yields than non-cover cropped years, controlling for weather. Here, cover crops show modest benefits of 0.65% and 0.35% for maize and soybean.

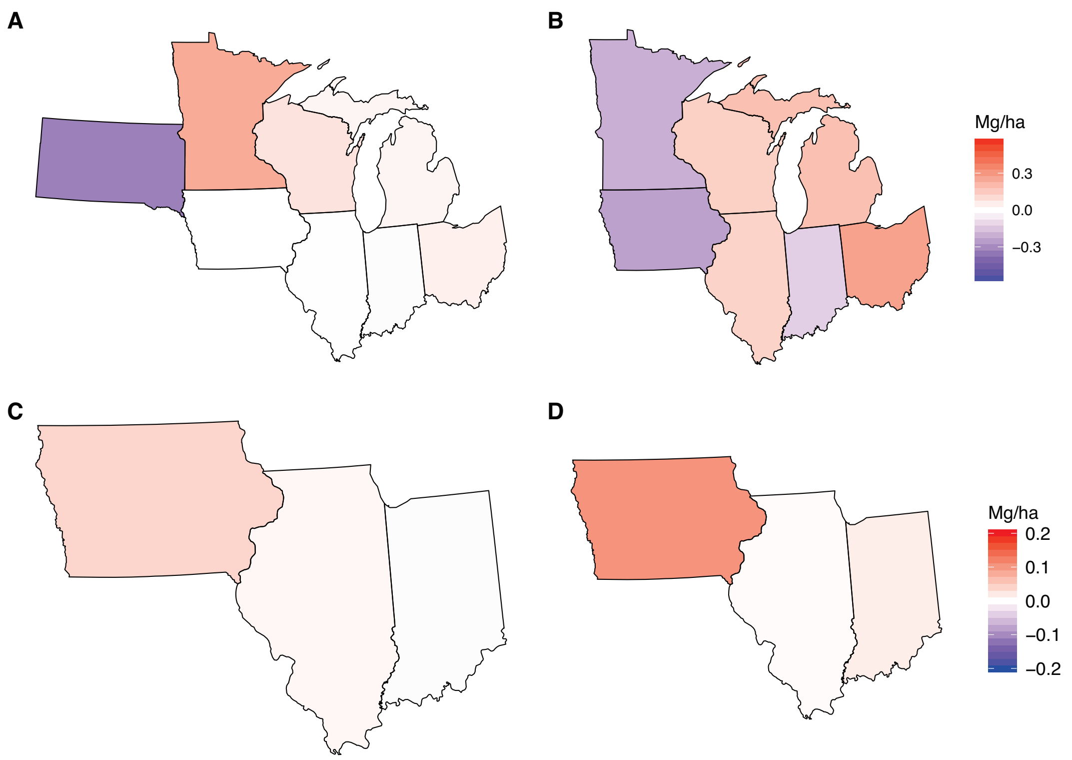

Figure 4. Yield effects of cover cropping for maize after one year (*a*) maize after three years (*b*) soybean after one year (*c*) soybean after three years (*d*). States shown indicate where both SCYM yields were available for the crop analyzed and where effects of cover cropping were significant at $p < .05$.

These benefits are comparable to [52] which found a 1.3% increase in maize yields, however, they are lower than the 3.8% soybean yield benefit reported. These numbers, however, were from a self-reported survey of growers following the practice so respondents may be vulnerable to a choice supportive bias [53] of cover crop adopters.

Cover cropping for multiple years does not appear to add a clear direction to the effects of the practice for maize. Three of the four states that benefit most with one year of cover cropping are also in the top four that benefit the most with three years, but large losses from cover cropping become apparent in other areas, potentially due to imperfect controls. However, for soybean longer periods of cover crop adoption did appear to increase benefits in most cases. Overall, the data one both one- and three-year yield effects on maize and soybean appear to indicate a lack of generalized economically large yield benefits to cover crops in the Midwest.

Caveats for the yield effects seen here include the fact that this analysis did not take into account cover crop type, found to have differential effects on yield by [54] and cultivar within a specific crop type, found to have differential effects by [55]. Additionally, yield outcomes in the analysis may be skewed toward zero by the inclusion of more cover cropped fields than actually present, adding noise to the regressions, or in a worst case, the classifier may in some places be detecting something other than cover crops (e.g. poor weed management) that has negative yield effects of its own. Issues with georeferencing across multiple years might add noise to the multi-year analysis disproportionately. Yield predictions for cover cropped fields may similarly be skewed by the prevalence of the practice on silage and/or seed maize fields versus maize for grain, especially in northern sections of the study area where maize grown for silage is more common [7]. In northeastern parts of the study area as well, snow and cloud cover in winter may make cover crop detection disproportionately more difficult (see supplementary materials). Also, our analyses of two-year adoption may be skewed low by growers who only use cover crops in conjunction with one of their cash crops in rotation, and thus regularly use cover crops, just not in consecutive years.

Despite these caveats, we believe that this is a valuable vein for future analysis, especially as both high-frequency satellite data necessary become more readily available and soil quality estimations improve with the additions of NCCPIv3, Fragile Soil Index, and soil susceptibility to compaction from future SSURGO versions. The source code for this study is made publicly available. (https://github.com/LobellLab/CoverCrop).

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