# Recent rapid increase of cover crop adoption across the U.S. Midwest detected by fusing multi-source satellite data

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Please contact the corresponding author if you have any questions or feedback about the manuscript, or if you would like early access to the dataset.

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**Key Points:**

- The first comprehensive field-level cover cropping in the U.S. Midwest from 2000 to 2021 is developed by a scalable remote sensing framework.
- Cover cropping acreage in the U.S. Midwest has significantly increased 3.3 times from 2011 to 2021, particularly a 63.6% increase in 2021.
- Cover crop adoption is primarily driven by federal and state incentive programs, and currently the overall adoption rate is only 7.2%.

## Abstract

Cover crops have critical significance for agroecosystem sustainability and have been long promoted in the U.S. Midwest. Knowledge of the variations of cover cropping and the impacts of government policies remains very limited. We developed an accurate and cost-effective approach utilizing multi-source satellite fusion data, environmental variables, and machine learning to quantify cover cropping in corn and soybean fields from 2000 to 2021 in the U.S. Midwest. We found that cover crop adoption in most counties has significantly increased in the recent 11 years from 2011 to 2021. The adoption percentage of the year 2021 is 3.3 times that of the year 2011, primarily driven by federal and state conservation programs. Particularly, the year 2021 has rapidly increased 63.6% of planting acreage compared to 2020, however, the percentage is still low (7.2%). Our work highlights the importance of incentives from the public and private sectors on promoting sustainable agricultural practices.

## Plain Language Summary

Cover crops typically grow after cash crop harvesting and before the following season's planting of cash crops, and can bring benefits to agricultural sustainability. To stimulate cover crop adoption in the U.S. Midwest, the U.S. government has made significant financial and technical support to growers for cover cropping (e.g. USDA Environmental Quality Incentives Program invested over $14 billion in conservative practices from 2010 to 2020). However, large-scale and long-term cover cropping information in the U.S. Midwest is largely missing. Timely and cost-effective monitoring and verification of cover crop adoption are urgently needed. We utilized multi-source remote sensing data and large amounts of ground truth data to develop effective approaches to detect cover crop adoption from 2000 to 2021 in a cost-effective manner. We found that cover cropping acreage has significantly increased 3.3 times from 2011 to 2021. Particularly, in the single year of 2021, cover cropping increased 63.6% to account for 7.2% of total corn and soybean croplands. We also found cover crop adoption is largely driven by federal and state conservation programs. The incentive programs from the public and private sectors are important for promoting sustainable agricultural practices to mitigate the impacts of climate change.


## 1 Introduction

Cover crops, such as cereal rye, oats, or clover grown after cash crop harvesting and before the following season's planting, can bring significant benefits to soil conservation (Plastina et al., 2020), nutrient management (Abdalla et al., 2019), weed control (Alonso-Ayuso et al., 2018), climate change adaptation and mitigation for agroecosystems (Delgado et al., 2021). The corn and soybean row crop system in the U.S. Midwest, contributing to one-third of the world's production (Rizzo et al., 2018), faces grand environmental challenges related to excessive use of fertilization (Jin et al., 2019), soil carbon loss (Thaler et al., 2021), and water quality degradation (Zhao et al., 2020). Cover crop adoption has been considered an essential solution to address these environmental challenges for sustainable agriculture (Seifert et al., 2018). However, the cover crop adoption percentage in the U.S. Midwest was very low (only 3.6% of cropland acreage in 2017) (NASS, 2012), primarily due to growers' concern about management complexity and economic viability of incorporating cover crops into current cropping systems (Roesch-Mcnally et al., 2018).

To stimulate more widespread adoption of cover crops, government efforts have been made at both Federal and State levels to provide financial and technical support to promote cover crop adoption. National conservation programs such as the Environmental Quality Incentives Program (EQIP) and the Conservation Stewardship Program (CSP) have significantly increased the proportion of grants towards cover crop cost-share programs(Wallander et al., 2021). Similar cost-share programs have also been launched in multiple states, for example, the Iowa Department of Agriculture and Land Stewardship (IDALS) provides a $25 per acre cost-share for first-time cover crop growers (Plastina et al., 2018). Besides cost-sharing, growers who plant cover crops are also eligible for a $5 per acre premium discount under the USDA Risk Management Agency (RMA) Pandemic Cover Crop Program and state-level counterparts. With more and more government support for the cover crop programs, the need for establishing quantifiable measures to evaluate the outcome of government funding is increasing. One clear challenge to achieving this goal is the lack of science-based, accurate, and cost-effective methods to detect long-term cover crop adoption on a large scale. The accurate estimates of current and historical cover crop acreages are essential for understanding cover crop adoption status and evaluating the outcomes of incentive programs.

Scalable and scientifically rigorous methods to quantify cover crop adoption at large-scale and long-period are highly needed. Field investigations are often deployed to identify cover crop adoption but are time-consuming, labor-intensive, and cost-prohibitive to scale up to large regions (Kc et al., 2021). Satellite remote sensing offers the opportunity to detect cover crop adoption in a cost-effective and scalable manner. However, existing remote sensing methods to detect cover crop adoption remain simple, generally lack validation, and are only applied in small regions without clear demonstration for scalable deployment (Barnes et al., 2021). These weaknesses result from the challenges related to weak cover crop signals, insufficient spatial and temporal resolutions of satellite data, and limited ground truth. Specifically, due to low winter temperatures, cover crops tend to be dormant and result in low accumulated biomass (Weil & Kremen, 2007). Obscured by soil and crop residue backgrounds, remotely sensed cover crop signals are often weak and difficult to identify (Bégué et al., 2018). For example, the widely used vegetation index threshold methods, e.g. Normalized Difference Vegetation Index (NDVI), are sensitive to soil backgrounds and can be hardly applied for large-scale cover crop detection without proper pre-processing (Rundquist & Carlson, 2017). Furthermore, satellite data have a trade-off between temporal and spatial resolutions. High spatial resolution satellite data, such as Landsat, can provide spatial details to detect field-scale cover crop adoption, but data availability is limited by the low revisiting frequency, cloud contamination, and snow cover in winter. Meanwhile, high revisiting frequency satellites, e.g. MODIS, have a coarse spatial resolution, which may not be enough for detecting field-scale adoption. In addition, to date, the ground truth data of field-level cover crop adoption are scarce. The existing cover crop detection algorithms heavily depend on ground truth data, and can be only performed locally, where ground truth data are sufficient (Bégué et al., 2018). Machine learning classifiers require large-volume and well-sampled ground truth data for model development and the performance could decrease dramatically in regions or periods beyond the training datasets (Barnes et al., 2021; Kc et al., 2021; Seifert et al., 2018).

Given these challenges for cover crop detection in general, a robust and scalable remote sensing framework needs to be developed with novel detection algorithms driven by domain knowledge, high spatial-temporal resolution satellite imagery, and with low dependence on ground truth data. To enhance cover crop signals, leveraging time-series satellite observations to capture the accumulated signals rather than a single satellite snapshot can be more effective (Barnes et al., 2021; Kc et al., 2021; Seifert et al., 2018). Regarding high spatial and temporal resolution remote sensing data, novel satellite fusion techniques, e.g. STAIR(Luo et al., 2018, 2020), which merges multi-source satellite data, e.g. Landsat and MODIS, to produce seamless, daily, and 30-m spatial resolution surface reflectance and potentially provide high-quality satellite data for detecting cover crop adoption practices. Particularly, such Landsat-MODIS fusion data set also can trace the long-term (e.g. back to the year 2000) change of cover crop adoption. Furthermore, the county-level census data is available for a few years (e.g. 2012 and 2017) and has good representation for counties across the Midwest. Incorporating such county-level census data to constrain remote sensing algorithms can facilitate model development and improve detection accuracy. While other sources of ground truth data can be used for further fine-tuning of models and independent validation.

The goal of this study is to develop a new and reliable framework (Figure 1) to detect cover crop adoption at field-scale across the U.S. Midwest from 2000 to 2021 using satellite data based on rigorous scientific foundations. The science foundation integrates the knowledge of cover crop plant agronomy and spectral features of different remotely sensed targets. We developed the following new solutions here: (1) to augment weak cover crop satellite signals, we utilized satellite time-series observations to extract the accumulated cover crop signal features by unmixing soil and cash crop signals based on their temporal characteristics; (2) we leveraged the advanced multi-source satellite fusion technique to integrate Landsat and MODIS to generate long-term (2000−2021), high spatial resolution (30 m), and high frequency (daily) data set for cover crop detection; (3) With satellite detected cover crop features, we developed machine learning models using environmental variables to predict thresholds of cover crop features for identifying cover crop adoption with the USDA county-level cover crop percentage census data as constraints. Cover crop growth is affected by multiple factors such as climate conditions (temperature, precipitation, vapor pressure deficit VPD), soil properties (clay, sand, silt, and soil organic carbon SOC), and geographic locations. Thus, the threshold for cover crop features changes over space and time, and it is crucial to use dynamic cover crop feature thresholds for large-scale and long-period cover crop mapping. Our threshold models considered climate, soil, and geographic location, on top of remote sensing derived growers' practice information (e.g. termination dates) to reduce the environmental impacts on cover crop detection. Based on our derived long-term cover crop adoption across the Midwest, we analyzed the temporal variability and the impacts of government policies on crop adoption to gain insights into how public policies promote sustainable agricultural practices.

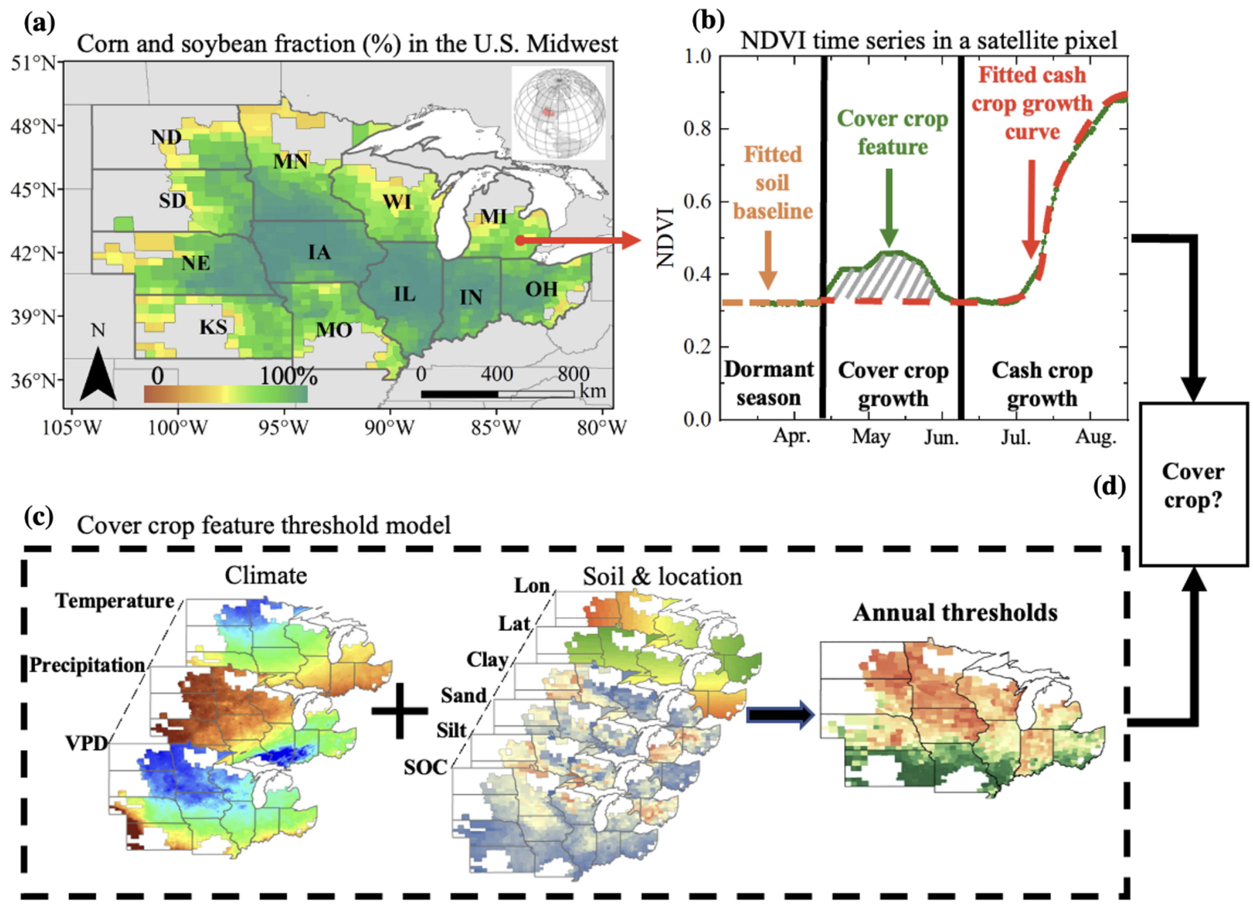


**Figure 1.** Conceptual framework for quantifying cover crop adoption in the U.S. Midwest using multi-source satellite fusion data. (a) Average corn and soybean fraction of each county in the U.S. Midwest from 2010 to 2020 (counties with corn and soybean cropland fraction < 40% are excluded). (b) We first utilized the STAIR fusion algorithm to merge Landsat and MODIS missions to generate daily and 30-m normalized difference vegetation index (NDVI) in the study region, and further extracted the NDVI time series from STAIR fusion datasets, showing the example of typical cover crop fields. By excluding soil backgrounds and cash crop signals, the accumulated NDVI signals (dashed region) are identified as cover crop features. Meanwhile, we utilized (c) the climatic variables (temperatures, precipitation, and vapor pressure deficit VPD), soil variables (clay, sand, silt, and soil organic carbon SOC), and geographic location to develop machine learning models to predict cover crop feature thresholds over space for each year. (d) By comparing the thresholds and cover crop features in each same satellite pixel, large-scale cover crop fields were identified.

## 2 Materials and Methods

The detailed framework to quantify cover crop adoption at a large scale and during a long period is shown in Figure S1. The framework includes four key parts: deriving high-quality NDVI time series, extracting cover crop features, modeling cover crop feature thresholds, and determining cover crop fields. The first part was done by applying STAIR to fuse Landsat and MODIS to obtain high spatial and temporal resolution satellite imagery from 2000 to 2021. Then we calculated the daily NDVI time series from STAIR fusion products. The details of generating STAIR fusion data can be found in Luo et al. (2018).

### 2.1 Extracting cover crop features

Remote sensing NDVI time series obtained from STAIR fusion data were used to extract cover crop features. Remote sensing NDVI time series for each satellite pixel were decomposed into soil (sNDVI), cover crop (cNDVI), and cash crop components (mNDVI), thus observed NDVI data at crop fields can be written as:

$$NDVI_d = sNDVI_d + mNDVI_d + cNDVI_d \tag{1}$$

where $d$ is the $d_{th}$ day of the year. Cash crops and cover crops have weak and negligible signals during the non-growing season, and bare soil contributes to almost all the NDVI signals during this period. The NDVI time series in the non-growing season is useful to detect the value of soil's impacts (Skakun et al., 2017):

$$sNDVI_d = min\{NDVI_d, d \in T_1\} \tag{2}$$

where $T_1$ is the non-growing season (before April 15th). After removing the soil signal, the NDVI time series consists of signals from cash crops and cover crops. Generally, cover crops are terminated before the harvest of cash crops. Thus, the NDVI time series during peak growing season is relatively "pure" cash crop signals. Based on crop vegetation phenology, the NDVI time series during peak growing season can determine cash crop signals by (Guan et al., 2014):

$$mNDVI_d = \frac{NDVI_p - sNDVI}{1 + exp(a - b * d)}, d \in T_2 \tag{3}$$

where $T_2$ is the peak-growing season (July and August), $NDVI_p$ is the NDVI signal during peak growing season, which equals to $max\{NDVI_d, d \in T_2\}$. The $a$ and $b$ are the remote sensing detected emerging day and the maximum growth rate of "pure" cash crops, respectively. Finally, the cover crop signal is extracted from the NDVI time series after separating the soil and cash crop signals. According to Eq. (1), the cover crop signal can be written as:

$$cNDVI_d = NDVI_d - mNDVI_d - sNDVI_d \tag{4}$$

The cover crop feature ($cSign$) or characteristic can be defined from the cover crop time series derived from Eq. (4), which is defined as:

$$cSign = \sum_{i=P1}^{P2} cNDVI_d, d \in T_3 \tag{5}$$

where $T_3$ is the growing season (from mid-April to July), P1 and P2 are remote sensing detected cover crop emerged and terminated dates. The date of P1 can be easily determined when removing the soil signal, which is the last day when NDVI value ($NDVI_d$) equals soil signal ($sNDVI_d$). The date of P2 is the first day when the NDVI value ($NDVI_d$) equals to cash crop signal ($mNDVI_d$).

### 2.2 Modeling cover crop feature thresholds

Cover crop growth varies dynamically across different regions and periods, which leads to dynamic cover crop features (Fan et al., 2020). The environmental factors are involved to predict the cover crop feature thresholds ($cThreshold$), which can be written as:

$$cThreshold = Function(environmental\ variables), d \in T_3 \tag{6}$$

where the model is established based on environmental variables and “ground truth”. The method can consider the influence of environmental factors on the cover crop mapping, which enables the capacity of the invention to be applied at large-scale and long-term with relatively high accuracy. In this study, the environmental factors include temperature, precipitation, VPD, clay, sand, and silt content, SOC, longitude, and latitude; the function is Random Forest. To augment label data for machine learning, the two-year NASS Census data in 2012 and 2017 are linearly interpolated to 2012−2017 and extrapolated to 2018 because precipitation in this year is outside the range of that in 2012−2017. With augmented label data sets, the developed threshold model is more reliable for quantifying cover crop feature thresholds from 2000 to 2021 in the U.S Midwest.

### 2.3 Validating cover crop maps

NDVI time series can obtain spatial- and temporal-specific cover crop features, and the environmental model can provide spatial- and temporal-specific cover crop feature thresholds. By comparing the cover crop features and thresholds, cover crop fields can be predicted. Specifically, satellite remote sensing provides cover crop features for each pixel, and the feature threshold model provides thresholds of cover crop determination. Using fine-scale field boundaries to mask pixel-level prediction, a field with 40% pixels predicted as cover crops is considered a cover crop field, and small fields (less than 150 m ×150 m) are excluded. These predicted cover crop fields from our framework are compared with field-level and county-level cover crop data from multiple sources for comprehensive validation.

## 3 Data

The datasets used to map cover crops across the U.S. Midwest in our framework includes cover crop data, satellite STAIR fusion data, environmental, and auxiliary data (Table S1).

The first category of datasets is the cover crop adoption data, which include the NASS county-level cover crop statistics from the USDA Census of Agriculture, and the field-level cover crop adoption data from multiple sources. The NASS county-level cover crop statistics are derived from the NASS Census of Agriculture in 2012 and 2017. The Census data cover all counties across the whole U.S. Midwest and have good spatial and temporal representations. Thus, this data set was used as ground truth for constraining the cover crop feature-threshold model (Figure 1c). The field data come from multiple sources including aircraft hyperspectral imagery identified cover crop fields, cover crop transect data from the Indiana State Department of Agriculture (ISDA), and reported cover crop fields from the USDA RMA that RMA paid a premium subsidy on cover crop fields (entire or part fields planted cover crops) reported by state programs (e.g. IDALS). The quality of field data may vary with sources and thus, we only used the field-level cover crop data for validation purposes. Specifically, we have deployed aircraft hyperspectral surveys (Wang et al., 2021) to cover parts of Illinois in 2020 and 2021. We accurately identified cover crop fields from 0.5 m aircraft hyperspectral images with the aid of field investigations. ISDA field-level data comes from ground vehicle-based transect surveys and covers the major parts of Indiana from 2015 to 2019, which provide GPS locations of cover crop fields nearby. Since the points are taken every half-mile, we assume the GPS location indicates cover crop fields within 400 m (Barnes et al., 2021). The USDA RMA dataset covers parts of cover crop fields in Iowa from 2018 to 2020 and in Illinois in 2020.

The second category of datasets is STAIR satellite data, which fused 16-day and 30-m Landsat observations and daily 500-m MODIS images to obtain a daily 30-m cloud-free dataset. The generated STAIR fusion data span from March 15$^{th}$ to August 15$^{th}$ from 2000 to 2021 and cover the whole U.S. Midwest. Then, we calculated the STAIR daily NDVI time series and extracted cover crop features for each field in the U.S. Midwest from 2000 to 2021.

The third category of datasets is environmental data, which includes PRISM climatic data and gSSURGO (Gridded Soil Survey Geographic Database) soil data. The PRISM climatic data (Daily Spatial Climate Dataset (Daly et al., 2015; PRISM Climate Group, n.d.) provides 2.5 arc minute temperature, precipitation, and VPD estimations for the U.S. Midwest since 1981, which were downloaded from Google Earth Engine (GEE). The gSSURGO soil data provide clay, sand, and silt content and soil organic carbon concentration (SOC) at 10 m resolution for the U.S, which were downloaded from the USDA-NRCS Geospatial Data Gateway website. The environmental datasets are used to develop cover crop feature threshold models.

The fourth category of datasets is auxiliary data, which includes NASS Cropland Data Layer, Corn and Soybean Data Layer, and field boundary layer. NASS Cropland Data Layer provides a 30-m cropland land cover type from 2008 to 2020 for the U.S. Midwest, which was downloaded from NASS CropScape. Corn and Soybean Data Layer provides 30-m corn and soybean products from 1999 to 2018 covering the U.S. Midwest, which was downloaded from GEE. We use our internal field boundaries as the polygon vectors for each field. The field boundaries are based on (Common Land Unit) CLU but with further refinement using CDL for each year. The auxiliary data are used to determine corn and soybean fields.

## 4 Results

### 4.1 Cover crop feature and its threshold for cover crop classification

Using the STAIR algorithm (Luo et al., 2018, 2020) to fuse Landsat and MODIS, we obtained daily, 30-m, and long-term (2000−2021) NDVI time series for all the corn and soybean fields in the Midwest (Figure 1a). As the example of one satellite pixel (Figure 1b), the time-series data were generated at the daily step for each year. We selected the spring period to detect cover crop adoption mainly because cover crops may not emerge in autumn and are often dormant in cold winters. Cover crops in the spring period (typically April and May) have relatively high biomass and could be easily detected. Meanwhile, a March 15$^{th}$ start could avoid snow signals in most areas of the study region and signals in March could be used for identifying soil baseline NDVI. Extending the NDVI time series to August 15$^{th}$ can be helpful to obtain the cash crop growth curve, which is used to differentiate the cover crop signal from the cash crop. We developed methods to decompose the observed satellite NDVI (the green curve in Figure 1b) into three components including the potential cover crop growth features, soil baselines, and cash crop growth curves (see Methods). Typically, before cover crop termination, cover crop growth leads to higher NDVI values in the period of April to May than the soil baseline. Specifically, the cover crop feature (the grey region in Figure 1b) was defined by subtracting satellite NDVI time series with the fitted soil baseline (minimum NDVI in March) and the cash crop growth curve (logistic regression curve from NDVI in June and July). As such, our approach utilized the accumulated NDVI values to augment the remote sensing signals of cover crops and avoided the irregular time for certain snapshots of satellite imagery (Barnes et al., 2021; Kc et al., 2021; Seifert et al., 2018). Furthermore, we aggregated the detected 30-m resolution cover crop pixels to the field scale with the fine-scale field boundaries (an improved version from the USDA Common Land Unit layer, See methods). Fields large than 150 m × 150 m with more than 40% cover crop pixels were identified with cover crop adoption practices. Compared to the conventional approaches of utilizing remote sensing snapshots (Kc et al., 2021; Plastina et al., 2018; Zhao et al., 2020), our approach can provide a more robust and accurate detection of cover crop adoption.

Given that the extracted satellite cover crop features vary with climatic variables and soil properties, and geographic locations, we derived feature thresholds for each satellite pixel to determine whether pixels have cover crops planted. Ideally, the thresholds should be zero if satellite observations are perfectly fitted. Due to the uncertainties of satellite data, cover crops lead to large features while non-cover crops have smaller features. We first inverted National Agricultural Statistics Service (NASS) county-level cover crop percentage census data to obtain feature thresholds for each satellite pixel. For the NASS inverted feature thresholds, environmental variables, e.g. air temperature, have a high correlation (Figure 2a). Furthermore, in the feature-threshold model, we included climatic variables (temperature, precipitation, and vapor pressure deficit), soil properties (soil clay, sand, silt content, and soil organic carbon), geographic location (longitude and latitude), and developed a Random Forest model. The model achieved high performance with $R^2 = 0.94$ and RMSE = 0.79 (Figure 2b) with the inverted thresholds from NASS county-level census data for ten-fold cross-validation. Specifically, the original NASS census data in 2012 and 2017 were interpolated to 2013–2016 and extrapolated to 2018 for data augmentation, and the county-level cover crop percentage data were inverted to identify the feature threshold for each satellite pixel (see Methods). The predicted spatially resolved annual cover crop thresholds are highly aligned with the thresholds inverted from NASS Census (Figure S2). Furthermore, we analyzed the relative importance of input variables (Figure 2c). Variables related to temperature (e.g. minimum, mean, maximum air temperature, and latitude) have the largest contributions to cover crop feature thresholds, followed by longitude and precipitation. The soil background has the lowest contributions, which may be attributed to two facts: (1) soil information is relatively stable across years, and (2) we defined soil baselines to reduce the influence of soil backgrounds.

To further explore the benefits of temporally dynamic thresholds rather than the commonly used fixed threshold (Amy Logan & Robin McNeely, 2021; Hagen et al., 2020; Rundquist & Carlson, 2017), Figs. 2(D) and (E) illustrate the validation results of predicted cover crop adoption of each county in 2017. Compared to the fixed thresholds for each county (Figure 2e, $R^2 = 0.23$), the spatially and temporally dynamics thresholds (Figure 2e) achieved much higher model predictive performance $R^2 = 0.63$. Moreover, using a single fixed threshold for the whole Midwest (Figure S3), the model performance in predicting cover crop adoption significantly degraded ($R^2 = 0.01$). This comparison demonstrated the importance of temporally and spatially resolved thresholds to detect large-scale cover crop adoption practices, and it is impossible to map cover crops interannually with fixed thresholds.

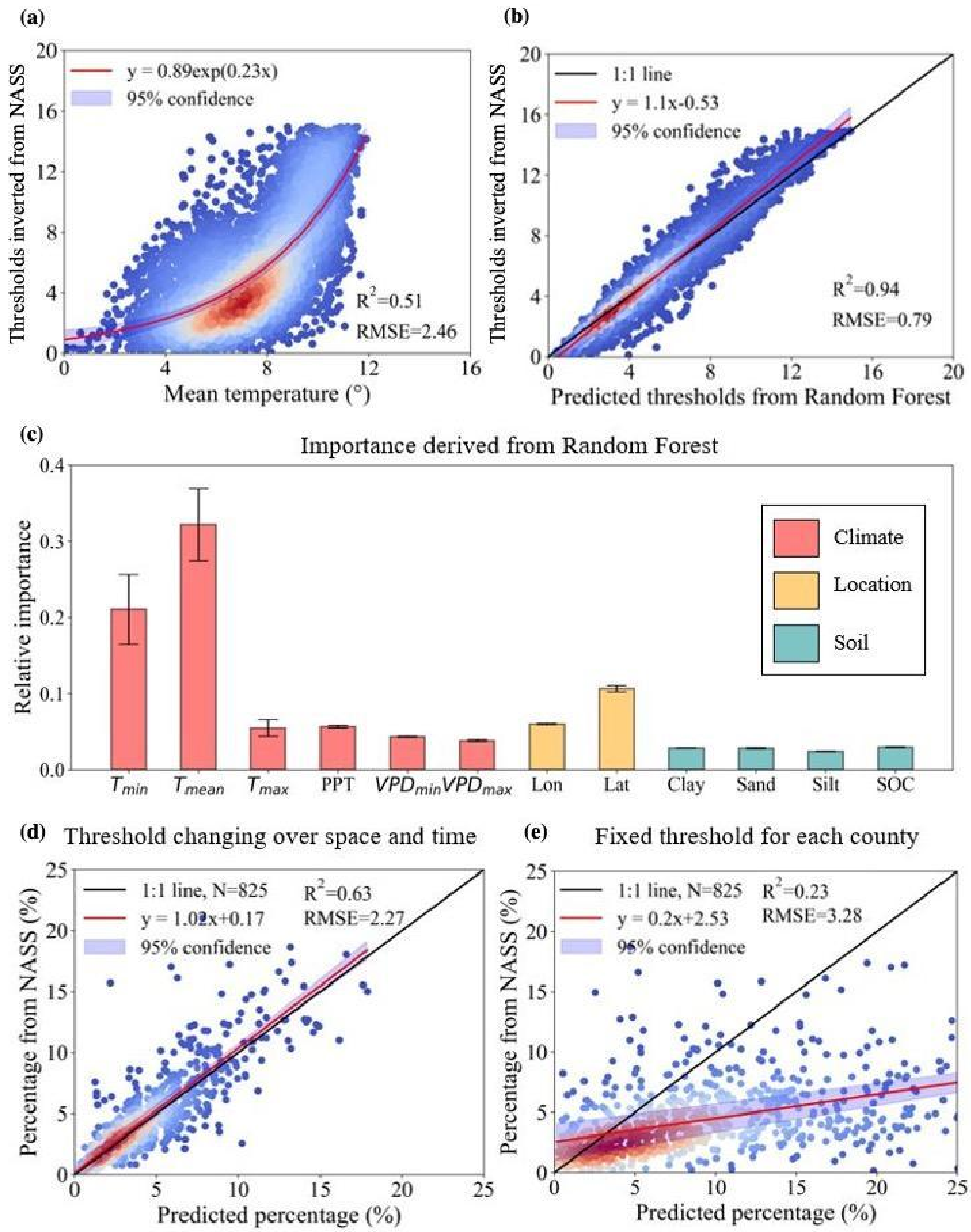


**Figure 2**. Model performance and relative importance of input variables for detecting cover crop adoption in the U.S. Midwest. (a) Relationship between NASS inverted thresholds and mean air temperature. (b) 10-fold cross-validation performance of predicting cover crop feature thresholds from environmental variables using Random Forest. (c) Relative importance of environmental variables (climate, soil, and geographic location) for predicting the thresholds. Higher values refer to higher importance. Performance of (d) dynamic and (e) fixed thresholds for predicting cover crop percentages of each county in the U.S. Midwest are validated against the NASS Census of Agriculture in 2017.

### 4.2 Cover crop adoption percentages

By comparing cover crop feature values derived from the STAIR NDVI time series and the environmental variable-based feature thresholds, Figure 2d shows the predicted cover crop percentages across the U.S. Midwest validated against the NASS report in 2017. The spatial patterns of predicted cover crop percentages from satellite observations are consistent with cover crop percentages from NASS reports (Figure 3a). At the county level, the predicted and NASS-reported cover crop percentages agree well in magnitude (Figure S4) with $R^2$s >0.6 and RMSEs <2.3. At the field level (Figure 3b), we also achieved high performance in detecting cover crop fields with aircraft hyperspectral surveys and field investigations in Champaign County, IL (accuracy of 87% in 2021), Indiana Cover Crop Transect surveys in La Porte County, IN (accuracy of 83% in 2019) and USDA RMA/IDALS cover crop fields in Mahaska County, IA (accuracy of 65% in 2020). The RMA data have slightly weaker validation performance partially because the RMA dataset was reported from growers and did not require the producer to plant cover crops in the entire field ( a producer received a cover crop premium subsidy for all or part of the field). If cover crops are planted in a small part of the field, which may result in weak satellite cover crop signals and lead to lower detection rates; while aircraft surveys and Indiana Cover Crop Transect surveys are from massive field investigations and have high credibility. Examples of comparisons between predicted cover crop fields and ground "truth" cover crop data are shown in Figure 3b. From satellite detection (Figure 3), cover crop adoption percentages are higher in the southeastern Midwest (Michigan, Ohio, Indiana, Iowa, Wisconsin, and Missouri) than those in the norther-western Midwest (North Dakota, South Dakota, and Minnesota). Furthermore, by excluding counties with corn and soybean field fractions less than 40%, 50%, 60%, 70%, 80%, and 90%, we found that correlations between prediction and NASS reports increase from 40% to 90% (Figure S4). Stronger relationships are obtained between prediction and NASS reports when keeping counties with higher fractions. In counties with dominant corn and soybean field fractions, predictions achieved higher performance (e.g. $R^2$ = 0.81 and RMSE = 1.25 for the corn and soybean fraction greater than 90%, Figure S4), indicating that our framework is well-suitable for detecting cover crop adoption in corn and soybean fields. While the model errors could be mostly from misclassification in field types other than corn and soybean. In these fields, the phenology of cash crops is different from typical corn and soybean phenological growth curves in Figure 1b.

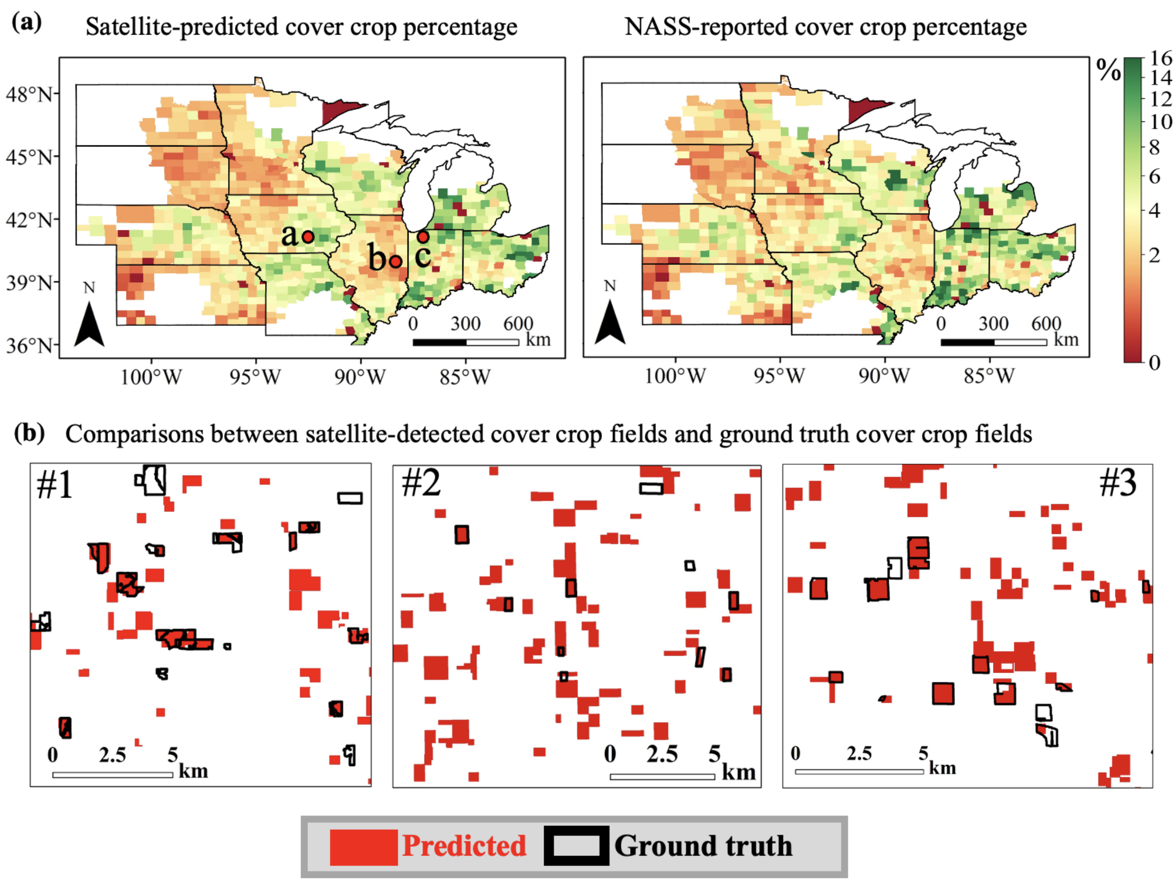


**Figure 3.** (a) Satellite-based prediction of cover crop percentage across the Midwestern Counties in 2017. (b) Field-level comparison of satellite-detected cover crop fields and ground truth data. #1: Mahaska County, Iowa in 2020; #2: Champaign County, Illinois in 2021; and #3: La Porte County, Indiana in 2019.

### 4.3 Cover crop adoption trends and their attribution

The detected cover crop adoption percentages at the county level across the study region show significant increasing trends from 2000 to 2021 (Figure 4a). Most counties show an increasing trend in cover crop adoption (Figures 4b and 4c). Meanwhile, the changes in cover crop adoption of counties in the U.S. Midwest from our prediction are highly consistent with those reported in the USDA NASS Census of Agriculture in 2017 (Figure S5). In the past two decades, the average annual increase rates for cover crop adoption are around 0.20%/yr and similar to previous studies (Hagen et al., 2020). The rapid increase in cover crop adoption in recent years is highly related to the increase in state and federal investment for cover crop practices or programs during the same period with an $R^2$ of 0.91 (Wallander et al., 2021). Furthermore, the Mann-Kendall test (Hamed, 2008) shows that the increased magnitude of cover crop adoption in the two periods (2000 to 2010 and 2011 to 2021) has the largest difference (each period longer than 5 years). The increase trend from 2000 to 2010 is not significant (p value=0.13>0.05), while there is significant increase from 2011 to 2021 (0.39%/yr and p-value <0.001) (Figure 4a). We found that government funding for cover crop cost-share programs increased from about $5 million in 2005 to about $156 million in 2018, particularly after 2015 (about $59 million). Meanwhile, in the second period, most states (except North Dakota, South Dakota, and

Minnesota) show obvious increase trends (Figure S6a), with Michigan, Ohio, Iowa, and Missouri leading the cover crop changes, which are consistent with USDA reports (Wallander et al., 2021). The different increases in cover crop adoption percentages among the states are highly related to the funding in each state for cover crops (Figure S6b). For example, Iowa provides a $25 per acre cost-share for the first-time cover crop adoption, which is one of the highest payment rates among others, and in conjunction with the Federal Crop Insurance Program, producers may qualify for an additional $5 per acre crop insurance premium subsidy (Plastina et al., 2018). The strong correlations between the increasing adoption percentages and Federal/State investments (Figures 4a and S6b) indicate that government investments in cover crops are an effective way to promote the adoption of cover crops.

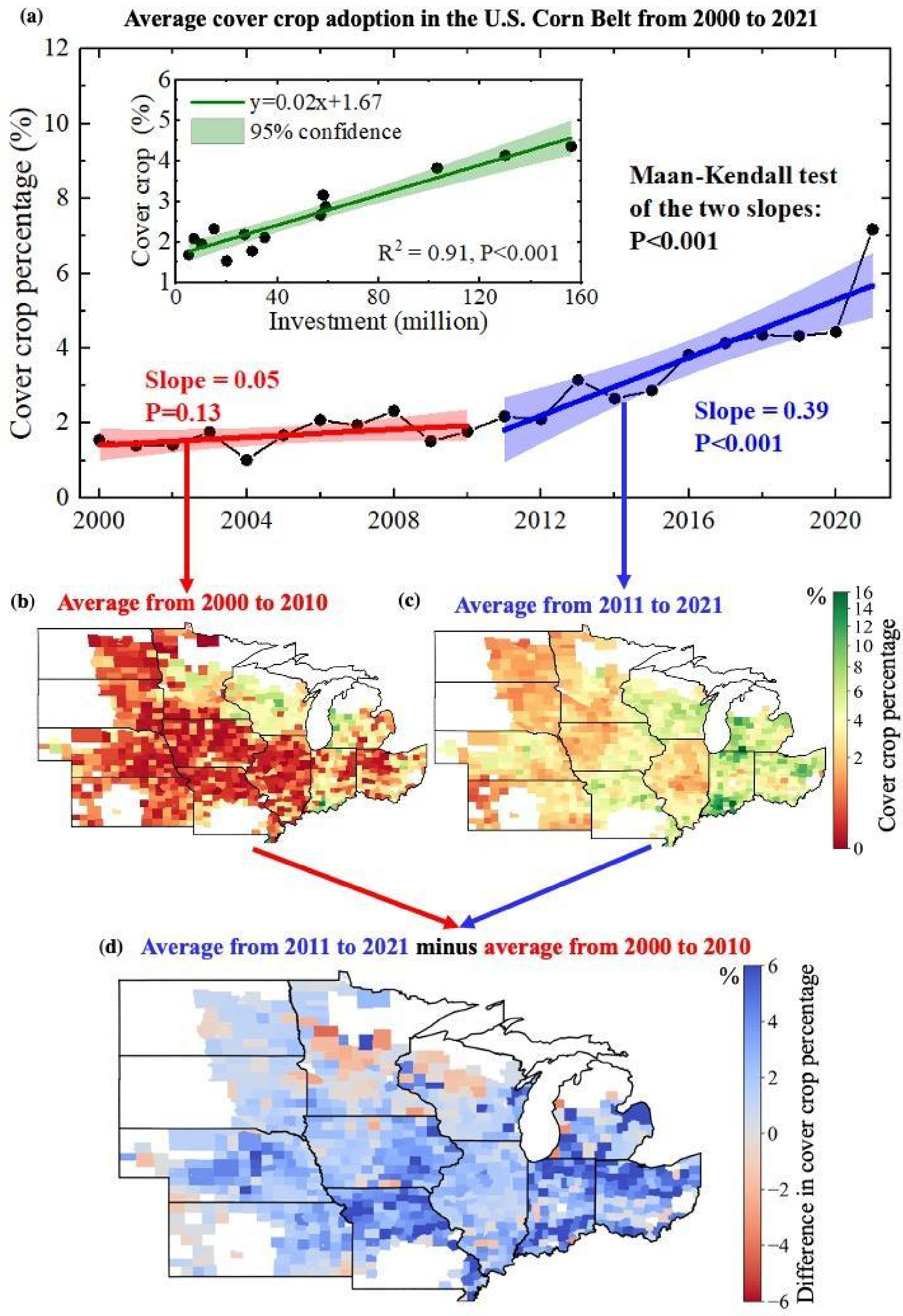


**Figure 4.** Cover crop adoption in the U.S. Midwest from 2000 to 2021 derived from STAIR fusion NDVI time series. (a) State-level average cover crop adoption rates (%) in the U.S. Midwest from 2000 to 2021. The Mann-Kendall test indicates that the periods should be divided into two parts (2000 to 2010 and 2011 to 2021). The increase of cover crops from 2000 to 2010 is negligible while there is a rapid increase from 2011 to 2021. The increase is highly related to

the government's investments in cover crop programs. (b) Average cover crop percentages of each county in the U.S. Midwest in 2000−2010. (c) Average cover crop percentages of each county in the U.S. Midwest in 2011−2021. (d) Cover crop adoption percentage change (%) of each county in the U.S. Midwest from 2000−2010 to 2011−2021. Note: investments in cover crops are obtained from USDA EQIP from 2005 to 2018 (Wallander et al., 2021).

## 5 Conclusions

Our study proposed and implemented a scalable framework to quantify cover crop adoption across the U.S. Midwest from 2000 to 2021 using the time series of multi-source satellite fusion data. Domain knowledge in plant agronomy (e.g. cover crop and cash crop phenology) and remote sensing was incorporated into the framework. Phonological features were derived from the annual daily NDVI time series after removing the soil influence in the early growing season and determining the cash crop features in the peak growing season. Thresholds for cover crop features were predicted by environmental factors including climatic and soil parameters, and geographical locations. National-scale county-level cover crop statistics from the NASS Census of Agriculture were used to train and validate the algorithm. Extensive validation is conducted at the field level using other various sources of data. Though remote sensing has been applied to map cover crops in previous studies (Barnes et al., 2021; Hagen et al., 2020; Seifert et al., 2018), it is challenging to apply these existing approaches at a large scale and for a long period. The dynamic thresholds changing over space and time, national and field-scale cover crop data for modeling and validation, make the framework feasible and robust for large-scale applications.

Although the environmental benefits of cover crops have been well-established in the scientific literature, the actual cover crop percentages in corn and soybean fields of the U.S. Midwest are still relatively low (Anderson-Wilk, 2008). The extra cost and risk related to cover crops are one of the biggest barriers for stakeholders to integrate cover crops into their existing cropping system (Roesch-Mcnally et al., 2018). Many university extensions [programs or educators] (Cholette et al., 2018; Council, 2012; Lee & McCann, 2019) have estimated an extra $20-30 cost increase for typical Midwest growers in terms of cover crop seeds and their termination. Hence, federal conservation programs (such as EQIP and CSP) and state counterparts (such as the program in Maryland) providing financial assistance (around $30-50 per acre) for planting cover crops, are critical to increasing the adoption percentage (Wallander et al., 2021). Our results reveal a recent increasing trend for cover crop adoption in the U.S. Midwest. Particularly, there is a huge increase in the percentage from 4.4% in 2020 to 7.2% in 2021. We believe such an increase is mainly due to the increasing government funding for cover crop practice incentives and programs, indicating the importance of government efforts in promoting cover crop adoption. However, with more government funding potentially directed in cover crop incentive programs, there is increasing pressure for governments to establish both quantifiable metrics to assess the benefits of these government investments and the capacity to conduct timely compliance checks on growers' cover crop planting activities. Our work paves the way to achieve these goals by offering a cost-efficient approach to establish the high-quality historical cover crop benchmark in reference periods (Hamilton et al., 2017) and to enable monitoring cover crop practices in real-time. Beyond supporting government policy design and improving the evaluation of government investments, our approach is also useful in quantifying the SCOPE 3 emissions (Hertwich & Wood, 2018) for grain users and food companies who rely on sourcing corn and soybean in the U.S. For example, a Midwest ethanol plant might be able to lower its carbon intensity score, if there is a reliable way to demonstrate an increasing cover crop adoption in its source area compared to a reference period. Similarly, a food and beverage consumer-packaged-goods (CPG) company that sources its ingredients from U.S. growers, could also more accurately assess the improvement of the carbon footprint in its supply chain by taking the increasing trend in cover crop adoption into consideration. Last, but not least, our approach could also offer a low-touch and reliable solution to gather historical and current cover crop adoption information needed for many agricultural carbon credit programs.

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**Data and materials availability**

The cover crop and STAIR fusion data that support the figures in this paper and other findings of this study are available from the corresponding authors upon reasonable request. RMA data is not publicly available under the disclosure agreements between RMA and University of Illinois. Other data supporting this study are properly cited and publicly available. The code of this study is available from the corresponding author upon reasonable request.

**References**

Abdalla, M., Hastings, A., Cheng, K., Yue, Q., Chadwick, D., Espenberg, M., et al. (2019). A critical review of the impacts of cover crops on nitrogen leaching, net greenhouse gas balance and crop productivity. *Global Change Biology*. https://doi.org/10.1111/gcb.14644

Alonso-Ayuso, M., Gabriel, J. L., García-González, I., del Monte, J. P., & Quemada, M. (2018). Weed density and diversity in a long-term cover crop experiment background. *Crop Protection*, *112*, 103–111.

Amy Logan, & Robin McNeely. (2021). Developing a Remotely Sensed Cover Crop Identification Tool. Retrieved January 29, 2022, from https://www.iowaview.org/cover-crop-mapping-project/

Anderson-Wilk, M. (2008). The gap between cover crop knowledge and practice. *Journal of Soil and Water Conservation*. Soil and Water Conservation Society.

Barnes, M. L., Yoder, L., & Khodaee, M. (2021). Detecting winter cover crops and crop residues in the midwest us using machine learning classification of thermal and optical imagery. *Remote Sensing*, *13*(10). https://doi.org/10.3390/rs13101998

Bégué, A., Arvor, D., Bellon, B., Betbeder, J., de Abelleyra, D., Ferraz, R. P. D., et al. (2018). Remote sensing and cropping practices: A review. *Remote Sensing*. https://doi.org/10.3390/rs10010099

Cholette, T. B., Soltani, N., Hooker, D. C., Robinson, D. E., & Sikkema, P. H. (2018). Suppression of glyphosate-resistant Canada fleabane (Conyza canadensis) in corn with cover crops seeded after wheat harvest the previous year. *Weed Technology*, *32*(3), 244–250.
Council, M. C. C. (2012). Midwest cover crops field guide. Purdue Extension. Purdue Extension Publication ID-433, West Lafayette, IN.
Daly, C., Smith, J. I., & Olson, K. v. (2015). Mapping atmospheric moisture climatologies across the conterminous United States. *PloS One*, *10*(10), e0141140.
Delgado, J. A., Barrera Mosquera, V. H., Alwang, J. R., Villacis-Aveiga, A., Cartagena Ayala, Y. E., Neer, D., et al. (2021). Potential use of cover crops for soil and water conservation, nutrient management, and climate change adaptation across the tropics. *Advances in Agronomy*, *165*, 175–247. https://doi.org/10.1016/bs.agron.2020.09.003
Fan, X., Vrieling, A., Muller, B., & Nelson, A. (2020). Winter cover crops in Dutch maize fields: Variability in quality and its drivers assessed from multi-temporal Sentinel-2 imagery. *International Journal of Applied Earth Observation and Geoinformation*, *91*. https://doi.org/10.1016/j.jag.2020.102139
Guan, K., Medvigy, D., Wood, E. F., Caylor, K. K., Li, S., & Jeong, S. J. (2014). Deriving vegetation phenological time and trajectory information over africa using seviri daily LAI. *IEEE Transactions on Geoscience and Remote Sensing*, *52*(2), 1113–1130. https://doi.org/10.1109/TGRS.2013.2247611
Hagen, S. C., Delgado, G., Ingraham, P., Cooke, I., Emery, R., Fisk, J. P., et al. (2020). Mapping conservation management practices and outcomes in the corn belt using the operational tillage information system (Optis) and the denitrification–decomposition (DNDC) model. *Land*, *9*(11), 1–23. https://doi.org/10.3390/land9110408
Hamed, K. H. (2008). Trend detection in hydrologic data: the Mann–Kendall trend test under the scaling hypothesis. *Journal of Hydrology*, *349*(3–4), 350–363.
Hamilton, A. v, Mortensen, D. A., & Allen, M. K. (2017). The state of the cover crop nation and how to set realistic future goals for the popular conservation practice. *Journal of Soil and Water Conservation*, *72*(5), 111A-115A.
Hertwich, E. G., & Wood, R. (2018). The growing importance of scope 3 greenhouse gas emissions from industry. *Environmental Research Letters*, *13*(10), 104013.
Jin, Z., Archontoulis, S. v, & Lobell, D. B. (2019). How much will precision nitrogen management pay off? An evaluation based on simulating thousands of corn fields over the US Corn-Belt. *Field Crops Research*, *240*, 12–22.
Kc, K., Zhao, K., Romanko, M., & Khanal, S. (2021). Assessment of the spatial and temporal patterns of cover crops using remote sensing. *Remote Sensing*, *13*(14). https://doi.org/10.3390/rs13142689
Lee, S., & McCann, L. (2019). Adoption of cover crops by US soybean producers. *Journal of Agricultural and Applied Economics*, *51*(4), 527–544.
Luo, Y., Guan, K., & Peng, J. (2018). STAIR: A generic and fully-automated method to fuse multiple sources of optical satellite data to generate a high-resolution, daily and cloud-/gap-free surface reflectance product. *Remote Sensing of Environment*, *214*, 87–99. https://doi.org/10.1016/j.rse.2018.04.042
Luo, Y., Guan, K., Peng, J., Wang, S., & Huang, Y. (2020). STAIR 2.0: a generic and automatic algorithm to fuse modis, Landsat, and Sentinel-2 to generate 10 m, daily, and cloud-/gap-free surface reflectance product. *Remote Sensing*, *12*(19), 3209.
NASS, U. (2012). Census of agriculture. *US Department of Agriculture, National Agricultural Statistics Service, Washington, DC*, *1*.
NRCS. (2020, October). U.S. Department of Agriculture. National Planning and Agreements Database (NPAD). Retrieved January 19, 2022, from https://www.nrcs.usda.gov/Internet/NRCS_RCA/reports/top-practices.html
Plastina, A., Liu, F., Sawadgo, W., Miguez, F., & Carlson, S. (2018). Partial budgets for cover crops in Midwest row crop farming. *Journal of ASFMRA*, 90–106.
Plastina, A., Liu, F., Miguez, F., & Carlson, S. (2020). Cover crops use in Midwestern US agriculture: Perceived benefits and net returns. *Renewable Agriculture and Food Systems*, *35*(1), 38–48. https://doi.org/10.1017/S1742170518000194

PRISM Climate Group, O. S. U. (n.d.). PRISM Gridded Climate Data. Retrieved January 31, 2022, from https://prism.oregonstate.edu

Rizzo, G., Edreira, J. I. R., Archontoulis, S. v, Yang, H. S., & Grassini, P. (2018). Do shallow water tables contribute to high and stable maize yields in the US Corn Belt? *Global Food Security*, *18*, 27–34.

Roesch-Mcnally, G. E., Basche, A. D., Arbuckle, J. G., Tyndall, J. C., Miguez, F. E., Bowman, T., & Clay, R. (2018). The trouble with cover crops: Farmers' experiences with overcoming barriers to adoption. *Renewable Agriculture and Food Systems*, *33*(4), 322–333. https://doi.org/10.1017/S1742170517000096

Rundquist, S., & Carlson, S. (2017). Mapping Cover Crops on Corn and Soybeans in Illinois , Indiana and Iowa, 2015-2016. *Environmental Working Group. Washington, D.C*, 2015–2016. Retrieved from www.EWG.org

Seifert, C. A., Azzari, G., & Lobell, D. B. (2018). Satellite detection of cover crops and their effects on crop yield in the Midwestern United States. *Environmental Research Letters*, *13*(6). https://doi.org/10.1088/1748-9326/aac4c8

Skakun, S., Franch, B., Vermote, E., Roger, J. C., Becker-Reshef, I., Justice, C., & Kussul, N. (2017). Early season large-area winter crop mapping using MODIS NDVI data, growing degree days information and a Gaussian mixture model. *Remote Sensing of Environment*, *195*, 244–258. https://doi.org/10.1016/j.rse.2017.04.026

Thaler, E. A., Larsen, I. J., & Yu, Q. (2021). The extent of soil loss across the US Corn Belt. *Proceedings of the National Academy of Sciences*, *118*(8).

Wallander, S., Smith, D., Bowman, M., & Claassen, R. (2021). Cover crop trends, programs, and practices in the United States. *U.S. Department of Agriculture, Economic Research Service*, (EIB 222).

Wang, S., Guan, K., Wang, Z., Ainsworth, E. A., Zheng, T., Townsend, P. A., et al. (2021). Airborne hyperspectral imaging of nitrogen deficiency on crop traits and yield of maize by machine learning and radiative transfer modeling. *International Journal of Applied Earth Observation and Geoinformation*, *105*, 102617.

Weil, R., & Kremen, A. (2007). Thinking across and beyond disciplines to make cover crops pay. *Journal of the Science of Food and Agriculture*, *87*(4), 551–557.

Zhao, F., Wu, Y., Wang, L., Liu, S., Wei, X., Xiao, J., et al. (2020). Multi-environmental impacts of biofuel production in the US Corn Belt: a coupled hydro-biogeochemical modeling approach. *Journal of Cleaner Production*, *251*, 119561.