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Review Paper

An examination of thematic research, development, and trends in remote sensing applied to conservation agriculture

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A B S T R A C T

Conservation agriculture seeks to reduce environmental degradation through sustainable management of agricultural land. Since the 1990s, agricultural research has been conducted using remote sensing technologies; however, few previous reviews have been conducted focused on different conservation management practices. Most of the previous literature has focused on the application of remote sensing in agriculture without focusing exclusively on conservation practices, with some only providing a narrative review, others using biophysical remote sensing for quantitative estimates of the bio-geo-chemical-physical properties of soils and crops, and few others focused on single agricultural management practices. This paper used the preferred reporting items for systematic review (PRISMA) methodology to examine the last 30 years of thematic research, development, and trends associated with remote sensing technologies and methods applied to conservation agriculture research at various spatial and temporal scales. A set of predefined key concepts and keywords were applied in three databases: Scopus, Web of Science, and Google Scholar. A total of 188 articles were compiled for initial examination, where 68 articles were selected for final analysis and grouped into cover crops, crop residue, crop rotation, mulching, and tillage practices. Publications on conservation agriculture research using remote sensing have been increasing since 1991 and peaked at 10 publications in 2020. Among the 68 articles, 94% used a pixel-based, while only 6% used an object-based classification method. Prior to 2005, tillage practices were abundantly studied, then crop residue was a focused theme between 2004 and 2012. From 2012 to 2020, the focus shifted again to cover crops. Ten spectral indices were used in 76% of the 68 studies. This examination offered a summary of the new potential and identifies crucial future research needs and directions that could improve the contribution of remote sensing to the provision of long-term operational services for various conservation agriculture applications.

1. Introduction

One of the greatest challenges of the 21st century is to increase food production without compromising soil and environmental quality. The key objectives of sustainable agriculture are to meet the food and fiber demand of a growing population while maintaining the quality of the soil and environment and providing sufficient profit to agricultural producers (Davis et al., 2012). Although simplification of the current cropping system and increased

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dependence on external inputs have improved the amount and quality of crop production worldwide, intensive agricultural practices also brought about degradation to the environment and slowly eroded and degraded much of the existing topsoil (Pittelkow et al., 2015). Tillage is one of the conventional agricultural practices responsible for soil loss from plowed agricultural lands (Thaler et al., 2021). Scientists realized that "worn-out" soils, whose productivity had declined, resulted mainly from the depletion of soil organic matter due to "tillage addiction" (Magdoff & van Es, 2009). Degradation from excessive tillage reduces soil health if best management practices are not adopted (Lehman et al., 2015). Since the end of World War II, agricultural policy, research, and the agricultural industry have focused on increasing food production for food security with little consideration to agricultural sustainability issues (Giovannucci et al., 2012). Following the Dust Bowl catastrophe of the 1930s, the U.S. policy focus on farm-level conservation was formed (Uri, 2001). Since then, soil regeneration techniques have drawn more attention to ensure the long-term sustainability of agricultural output through the use of best management practices (Baumgart-Getz et al., 2012; Prokopy et al., 2019).

The three pillars of conservation agriculture seek to address different agricultural problems. The three pillars are: 1) use no-tillage or minimum-tillage practices, 2) cover the soil surface with crop residue, and 3) use diverse crop rotations (Brye & Pirani, 2005; Sharpley et al., 2015). No-tillage leaves plant parts or crop residue after a crop is harvested in the field as soil cover. Soil microorganisms increase rapidly after conversion to no-tillage and help decompose the crop residue and build soil organic matter. No-tillage also decreases soil erosion by wind and water (Claassen et al., 2018; Huggins & Reganold, 2008). Cover crops can act as a weed suppressor if planted in seasons between commercial crops. The cover crops are mowed or terminated before or during subsequent plantings, which helps suppress unwanted weeds and provides nutrients to the soil as they decay (Hartwig & Ammon, 2002; Teasdale, 1996). Additionally, the use of diverse crop rotations can help reduce insect pests and other plant pathogens. A diverse crop rotation helps to break up the plant-pathogen cycle and competition, thus helping to reduce the need for pesticides (Bullock, 1992; Chamberlain et al., 2020). The benefits of adopting all three conservation agriculture techniques jointly are an increase in soil health, which includes building soil organic matter, reducing soil compaction, decreasing erosion, rebuilding soil aggregates, increasing water holding capacity, and increasing water infiltration. In the long term, these practices may help to increase crop yields and possibly cut input costs and the system's energy footprint, thus improving agricultural and environmental sustainability (Magdoff & van Es, 2009). Therefore, the assessment and identification of best agricultural management practices are essential for sustainable agriculture. Data from satellite, airborne, and drone sensors can now be combined with ground data to repeatedly map and measure a range of vegetation and soil properties required for the three pillars of conservation agriculture.

Remote sensing technologies have been useful and effective in assessing and monitoring agricultural practices (Khanal et al., 2017). Farmers and researchers can observe their fields, crops, yield, and production practices without physically visiting or inspecting them. Due to the recent development of multispectral (3–10 wider bands) and hyperspectral (hundreds of narrow bands) sensors onboard different satellite platforms (Landsat, Sentinel, and others) and unoccupied aerial vehicles (UAV), the spectral and temporal properties of agricultural land surfaces can be monitored with high spatial and temporal resolution. As remote sensing in agriculture has a wide range of applications, specifying categories is important. Applications, platforms, sensors, location, and context are the five aspects that should be addressed or included when using remote sensing techniques in agricultural research, according to a remote sensing meta-review on agriculture by Weiss et al. (2020). In recent years, the popularity of using remote sensing has increased mainly due to a significant increase in publicly available, fully corrected global satellite archives and associated online processing. However, using remote sensing techniques is not straightforward and requires knowledge and skills in processing remotely sensed data for meaningful result interpretation.

Among the existing remote sensing platforms, different satellite- and UAV- derived multispectral and hyperspectral data have been widely used in agricultural research (Candiago et al., 2015; Govender et al., 2008; Hunt & Daughtry, 2018; Maes & Steppe, 2019; Radočaj et al., 2020). Due to recent improvements in sensor development, UAVs have been widely adopted in the precision agriculture domain. The unoccupied aerial vehicles are equipped with high-resolution sensors and used mainly for field-level data collection. The unoccupied aerial vehicles have many applications, including crop yield estimation (Feng et al., 2020; Nevavuori et al., 2019, 2020; Stroppiana et al., 2015; Yang et al., 2021), assessment of soil moisture (Aboutalebi et al., 2019; Ge et al., 2019; Hassan-Esfahani et al., 2015; Luo et al., 2019), weed identification (Dian Bah et al., 2018; Hung et al., 2014; Lan et al., 2021), vegetative growth monitoring (Al-Ali et al., 2020; Burns et al., 2022; Tao et al., 2020; Zhang et al., 2020), water and irrigation mapping (Chao et al., 2008; Shi et al., 2019), crop identification (Chew et al., 2020), crop phenology (Yang et al., 2017, 2020), and others. Although UAVs have many useful applications in agriculture, the limitations are that quality UAVs are costly and flight duration largely depends on payload, weight, and internal configurations (Adão et al., 2017; Delavarpour et al., 2021). By contrast, free access to Landsat, Sentinel, MODIS, and other satellite archives has revolutionized satellite images, especially in conservation agriculture (Liu et al., 2020; Wulder et al., 2019). Many studies use free satellite imageries for land-use monitoring and change detection (Al-Juboury & Al-Rubaye, 2021; Chen & Wang, 2010; Chughtai et al., 2021; Fonji & Taff, 2014), crop identification and mapping (Belgiu & Csillik, 2018; Xun et al., 2021; Yan et al., 2021), phenology mapping using time series (Li et al., 2021; Schreier et al., 2021; Zhao et al., 2021) and other applications. In addition to access to free satellite imagery, many private satellite companies, like Planet Lab, provide high spatial and temporal resolution time series imagery for a fee (Huang & Roy, 2021). The type and use of satellite images mainly depend on the research objectives.

Another important aspect of remote sensing is using different statistical, machine learning algorithms, and biophysical models to classify satellite images by transforming pixel values to quantify key properties, such as plant biomass and soil moisture, for agricultural research. Using pixel- (Kc et al., 2021; Martins et al., 2021) and object-based classification methods (Ding et al., 2021; Najafi et al., 2021), researchers seek to understand, identify, detect, and map different agricultural conservation practices. Researchers can use a variety of Spectral Indices (SIs) such as the Normalized Difference Tillage Index (NDTI), Normalized Difference Senescent Vegetation Index (NDSVI), Shortwave Infrared Normalized Difference Residue Index (SINDRI), Normalized Difference Residue Index (NDRI), Enhanced Vegetation Index (EVI), and Normalized Difference Vegetation Index (NDVI), to identify, model, and infer crop and soil surface information. Among the indices, the NDVI is widely used and misused in many agricultural studies (Estrella et al., 2021; Ustuner et al., 2014). A new modified version of NDVI called kernel NDVI (kNDVI), which can reduce the mixed pixel issue (Camps-Valls et al., 2021), is helpful in agricultural research and may generate intriguing results. The SIs are computed by adding and subtracting different image bands, such as red, green, blue, near-infrared, and others, by emphasizing a particular property while omitting other features. The indices are frequently used to improve the classification algorithm's accuracy. In agriculture, the reflectance of light changes with chlorophyll content, water content, plant type, sugar content within tissues, and other factors. Indices enhance the spectral information and increase the separability of the classes of interest. Various classification algorithms such as Random Forest (Barnes et al., 2021; Seifert et al., 2019), regression models (Thieme et al., 2020; Van Deventer et al., 1997; Viña et al., 2003), Spectral Unmixing (Chi & Crawford, 2014; Laamrani et al., 2020; Pacheco et al., 2008; Pacheco & McNairn, 2010), Thresholding (Hively et al., 2018, 2020; Liu et al., 2018; Nowak et al., 2021) and other techniques, have been used in solving various identification, classification, and prediction problems in conservation agriculture. The use of single and/or multiple methods and algorithms is largely dependent on the topic of interest. Several field-level experimental research studies and reviews have been published on conservation agriculture practices globally (Ahmad et al., 2020; Prokopy et al., 2019), and some research reviews incorporate remote sensing techniques in agriculture in general (García-Berná et al., 2020; Lizotte et al., 2021; Weiss et al., 2020). A few review articles have focused on two vitally important biophysical variables, such as plant biomass and soil moisture (Ali et al., 2015; Babaeian et al., 2019; Ge et al., 2011; Lausch et al., 2019). A limited number of reviews have focused on some key topics, such as precision and smart farming in agriculture using remote sensing techniques (Khanal et al., 2017; Navarro et al., 2020). Biophysical remote sensing models use data collected by satellite and other remote sensing technologies to estimate various biophysical parameters of Earth's surface, such as vegetation cover, canopy height, and leaf area index. These models are important in conservation agriculture because they provide information on the health and productivity of crops, which can help farmers make informed decisions about management practices that can improve soil health and reduce erosion. In addition, researchers and scientists use biophysical remote sensing models to study the relationship between land management practices and their impact on the environment. By analyzing data from these models, they can better understand the effects of different management practices on soil health, water quality, and other key environmental indicators and explore the systems for the retrieval of bio-geo-chemical-physical variables from satellite remote sensing imagery (Ali et al., 2015; Babaeian et al., 2019; Ge et al., 2011; Lausch et al., 2019). However, during a thorough literature evaluation, no categorical or thematic examination of remote sensing exclusively focused on conservation agriculture practices and its principles were identified.

Given its importance, this study provides an examination of remote sensing techniques, methods, and processes used particularly for conservation agriculture. As a result, existing literature that applies any conservation practices, as well as some predefined inclusion and exclusion criteria, were chosen after searching the literature that is currently accessible. Due to the heterogeneity of study articles, a statistical meta-analysis is not provided. Furthermore, though an essential component of conservation agriculture, the specific separation of biophysical remote sensing models for quantitative estimates of bio-geo-chemical properties of soils and crops was beyond the initial intended scope of this study. Instead, qualitative results on article metadata and the data extracted from selected papers on some key variables of interest are presented without statistical comparison across methods or results; however, citations of related reviews and articles for readers are provided when necessary.

The main goal of this literature examination is to provide a general overview and trends of remote sensing methods applied in conservation agriculture research. To accomplish the goal, this paper was guided by the main research question: How are remote sensing tools, techniques, algorithms, and methods applied to conservation agriculture? This study is unique in that a diverse array of studies from various regions and countries have been gathered and examined, offering a summarization and global perspective on remote sensing tools, techniques, and methods used in five essential conservation practice categories, which were not addressed in past reviews. By highlighting gaps in the existing literature and offering recommendations for future research, our evaluation serves as a valuable resource for the development of more advanced and efficient remote sensing tools, techniques, and methods tailored especially for conservation agriculture and its three principles. Further, this study adopted the PRISMA methodology and distinct keywords related to conservation agriculture and remote sensing, ensuring the findings draw from high-quality evidence that exclusively focuses on the intersection of both conservation agriculture and remote sensing, setting this examination apart from previous works. This assessment presents trends and standards for evaluating remote sensing tools, techniques, and methods to date, making it a valuable resource for researchers, policymakers, and other stakeholders interested in using remote sensing as a tool for conservation agriculture, an aspect not fully explored in earlier reviews.

2. Principle and typology for conservation agriculture

Conservation agriculture is an agricultural management system that promotes minimum soil disturbance using no-tillage or conservation tillage, maintenance of ground cover using crop residue, cover crops, or mulching, and crop diversification through crop rotations and intercropping (Hobbs et al., 2008; Page et al., 2020). In the long term, the process helps rebuild soil biological processes, contributes to minimizing soil erosion, and ultimately increases agricultural production. This paper describes conservation agriculture in terms of its underlying three fundamental principles (Fig. 1). Conservation tillage is defined in terms of no-tillage and minimum tillage. Soil or ground cover is defined as a cover crop, crop residue, and mulching. Crop diversification is defined as crop rotation, crop mix, and intercropping. However, in some cases, well-grounded judgment was used in grouping those conservation practices by article type. For data analysis and visualization, all conservation practice information extracted from the selected articles was grouped into five major categories: cover crop, crop residue, crop rotation, mulching, and tillage practice.

3. Materials and methods

3.1. Information sources and search strategy

Literature from three established databases, including Clarivate Analytics Web of Science core collection via University of Arkansas library, Elsevier's Scopus database via Pisa University Library, and Google Scholar database were used to prepare this examination. Web of Science covers more than 20,000 peer-reviewed journals from more than 250 fields of study with a temporal coverage from 1900 to the present year. Scopus has more than 23,000 peer-reviewed journals from more than 23 major disciplines. It is uncertain how many journals or over what period Google Scholar has publications. The final search was performed on December 3rd, 2021.

An important step in any systematic literature search process is defining key concepts and associated search keywords. Most databases like Web of Science, Scopus, and Google Scholar use keywords with Boolean operators and wildcards. Boolean syntax acts as a search engine that allows users to combine keywords with

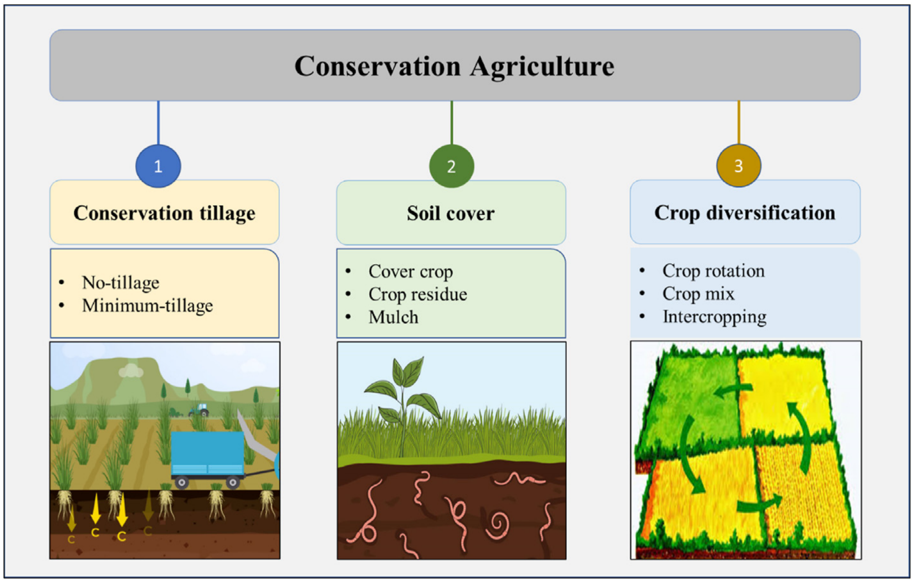

Fig. 1. Three principles of conservation agriculture (Sources: panel 1: https://bit.ly/35cE4x0, panel 2: https://bit.ly/3AuxZYo, panel 3: https://bit.ly/3rHYSEb).

operators such as AND, NOT, and OR to generate more relevant results. In contrast, wildcards are characters, such as an asterisk (*), which can be used to add spelling variations and derivatives of a keyword without having to input them all separately. The combination of concepts and keywords is often called search strings, which was used to search and retrieve relevant literature from the database. Keywords related to the application of remote sensing tools, techniques, methods, algorithms, and indices in conservation agriculture and variations of words associated with the topic of interest were used in such a way that only those articles that matched the research objective were identified. The keyword search was performed only on article titles rather than the abstract or the whole manuscript. This strategy helped to get topic-specific literature and reduced false-positive articles for final selection. The keywords and concept-wise search strings are presented in Table 1.

The literature search process used the combination of “OR” and “AND” as Boolean operators. Concept 1: remote sensing and concept 2: conservation agriculture using the operator “AND” requires that at least one keyword of each concept must appear in the article title to be selected for screening. Additionally, the operator “OR” was used to find articles that included any keywords in the article title. The “OR” operator helps broaden the search and captures all the related articles on the topic of interest. Several search strings were developed and refined using several rounds of trial-and-error processes so that only relevant papers were identified via database searching. The keywords used were selected after an extensive literature search of existing articles on remote sensing and conservation agriculture. It is important to note that different search strategies using different keywords and inclusion and exclusion criteria may result in a different number of articles, and it is solely dependent on researchers and their research objectives. Efforts were made to find all related literature and record information accordingly, but some articles may not have been selected due to the constraints mentioned above.

Table 1
Search queries designed for getting articles from databases.

Key concepts and keywords	
Concept 1: Remote Sensing	Concept 2: Conservation Agriculture
remotely sensed satellite image*	conservation cover crop residue tillage* no-till crop rotation mulch* soil conservation soil cover multi-cropping buffer strips contour buffer strips contour farming intercropping cropping pattern

3.2. Preferred reporting items systematic reviews and meta-analyses (PRISMA)

The PRISMA methodology and protocol framework version 2020 was used in this current work (Page et al., 2021) (Fig. 2). PRISMA is a structured protocol that guides systematic literature reviews and supports the reporting of step-by-step processes of different phases of the systematic review. PRISMA has three main sections: i) identification of the total number of articles from different databases; ii) screening of identified articles using inclusion and exclusion criteria and the reason for exclusion of studies; and iii) reporting the total number of articles that have been both included and reported in the review paper (Page et al., 2021). This framework helps researchers ensure transparency in each step of the review process (Liberati et al., 2009; Moher et al., 2009). The PRISMA framework has been used extensively by health and medical researchers. Due to its unique characteristics and transparency in research steps, PRISMA is now being used in many disciplines, including finding more comprehensive applications as is the case with remote sensing in the agricultural field (Adu et al., 2018; Koutsos et al., 2019; Navarro et al., 2020).

3.3. Eligibility, exclusion criteria, article screening, and selection

To obtain a robust number of articles for evaluation and data extraction, several inclusion and exclusion criteria were utilized.

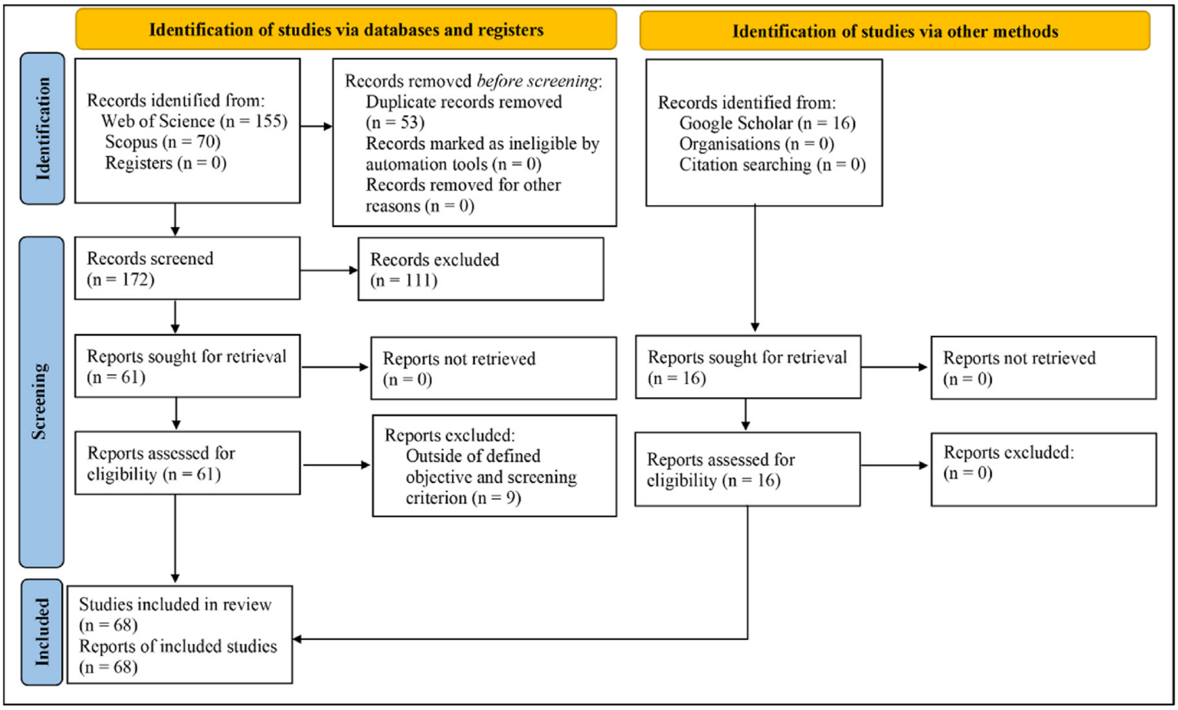

Fig. 2. PRISMA 2020 flow diagram for the systematic review of remote sensing for conservation agriculture [adapted from Page et al. (2021)].

Only peer-reviewed articles written in English and without any year-of-publication restriction were searched for. Any articles that were not peer-reviewed were discarded from the search process. After setting up inclusion and exclusion criteria, 225 peer-reviewed journal articles from the Web of Science and Scopus databases were identified. Out of the 225 articles, 155 and 70 were derived from Web of Science and Scopus databases, respectively. Using the Google Scholar search, another 16 articles were identified that were not identified using keyword searches from the databases above. A duplication check was conducted using Excel® and led to the elimination of 53 articles, leaving 172 articles combinedly from the Web of Science and Scopus database, plus 16 articles from the Google Scholar search. Screening of abstracts of the remaining 188 papers using the following additional criteria led to the exclusion of an additional 111 articles that did not meet the research objective and screening criteria. Abstract screening involved: (1) whether or not identified articles were related to conservation agriculture and/or soil conservation field and have applied any remote sensing methods; (2) exclusion of studies other than conservation agriculture and/or soil conservation such as erosion, soil moisture, water, forestry, and biodiversity; (3) inclusion of articles that had at least one conservation agriculture keywords from Table 1; and, (4) articles using either satellite- and/or UAV- derived data. After abstract screening, 77 articles were downloaded as full-text articles. After reading all articles, an additional nine articles were determined to be outside of the screening criteria leaving 68 (36.17%) articles for data extraction. While this study focuses on the articles themselves, future research may want to disaggregate between such attributes as author affiliation (public vs. private sector), author discipline, and other demographic variables.

In the identification phase, 225 articles were identified with the search tools. Among those, 53 articles discovered to be present in both databases and were eliminated. Following the previously indicated screening criteria, a manual assessment of the articles was carried out during the screening phase to determine whether article titles adhered to the aims provided for this study. Out of the 188 articles, 120 (63.83%) were deemed invalid and eliminated because they did not fit the research aim and screening criteria. Only 7 (5.73%) of the 120 publications were non-English, and the remaining articles did not consider remote sensing and conservation agriculture to be the primary focus of the study. Obvious limitations exist by not including those articles which were non-peer-reviewed and not in English. That being said, by using the PRISMA framework with our parameters (peer-reviewed and in English) this constitutes a representative sample of work.

3.4. Data extraction

For each selected article, article metadata for further descriptive analysis were collected. Latitude and longitude information were collected from the study or from the centroid of the respective country. Aside from metadata extraction, key variable information from each article was collected (Table 2). As shown, both qualitative and quantitative information were recorded from the selected articles.

4. Results

The results of this examination were compiled and discussed using the database mentioned above. The results pertain to the research period between 1991 and 2021.

4.1. Number of conservation agriculture papers published by year

The trend of conservation agriculture research publications using remote sensing is upward (Fig. 3), with a noticeable increase in publications after 2007. In 2020, the maximum number of articles published per year (10) occurring, with half of the total published after 2015.

Table 2
Attributes and variables used for data extraction from the selected papers.

Number	Attribute	Type	Key categories/description
1	Paper id	Numeric	Total number of articles (1-68)
2	Conservation practice type	Text	Cover crop; Crop residue; Crop rotation; Mulching; Tillage practices
3	Data types	Text	Optical; Radar
4	Satellite/sensor type	Text	Landsat; Sentinel; Moderate Resolution Imaging Spectroradiometer (MODIS); Satellite Pour l'Observation de la Terre (SPOT); Airborne Visible/Infrared Imaging Spectrometer (AVIRIS); Advanced Spaceborne Thermal Emission and Reflection Radiometer (ASTER); Unoccupied Aerial Vehicle (UAV); Vegetation and Environment monitoring on a New Micro-Satellite (VENuS); WorldView; and others
5	Spatial resolution	Numeric	Recorded in meters
6	Spatial resolution type	Text	Low; Medium; High
7	Number of bands/ features	Numeric	Total number of bands/feature each study used
8	Indices/index type	Text	Normalized Difference Vegetation Index (NDVI); Cellulose Absorption Index (CAI); Soil-adjusted Vegetation Index (SAVI) and others
9	Classification method type	Text	Pixel-based; Object-based
10	Classification algorithm type	Text	Random Forest (RF); Maximum Likelihood; Support Vector Machine; Spectral Unmixing Algorithm, Threshold-based Algorithm; Object-based Algorithm; Logistic Regression and others.
11	Accuracy	Numeric	Range from 65% to 98%
12	Crop species	Text	Different species of crops used in each study

4.2. Number of conservation agriculture papers and classification method types

Pixel-based classification methods were used in most of the conservation agriculture papers. Among the 68 articles, 64 (94%) papers used the pixel-based classification method, and only 4 (6%) used the object-based classification method.

4.3. Conservation agriculture practices and classification method types

Of the 64 studies using pixel-based classification, 23 were on crop residue practices, followed by cover crops, tillage practices, and crop rotation (Fig. 4). Only four studies reported the use of pixel-based classification for mulching. Four studies used object-based classification; that method was used on crop residue and cover crop studies. By combining classification methods, conservation practices, and paper id, the count was calculated. In certain contexts, object-based classification yields better accuracy than pixel-based classification because the method utilizes the latest image segmentation techniques, which first groups image pixels into spectrally homogenous picture objects before classifying the individual objects (Guo et al., 2007).

4.4. Conservation agriculture paper citations by year grouped by classification method types

Most citations recorded the use of pixel-based classification compared to object-based classification. Pixel-based methods started in 1995, whereas object-based citations were not found until 2012. The temporal trend across years showed that citation count has a downward in recent years. This should not be surprising, given that older articles have a greater chance for citation.

4.5. Number of conservation agriculture papers and classification algorithm types

Among the 68 articles, 52 (76%) reported using one or more classification algorithm types (Fig. 5). In contrast, 16 (24%) of the publications used various reflectance/spectral-based techniques, which were not included as classification algorithms since they were not regarded as classification algorithms. Of the classification

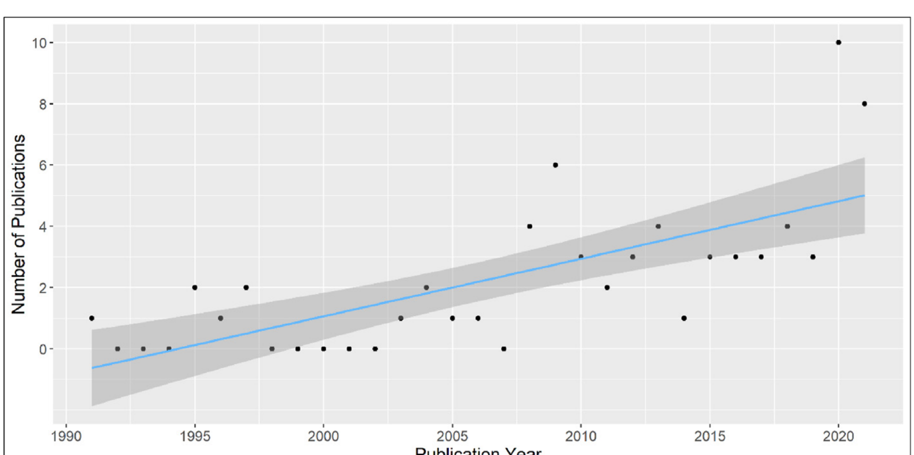

Fig. 3. Number of conservation agriculture papers published per year using remote sensing from 1991 to 2021. [Blue line represents the trend line, and the grey-shaded area represents the 95% confidence interval].

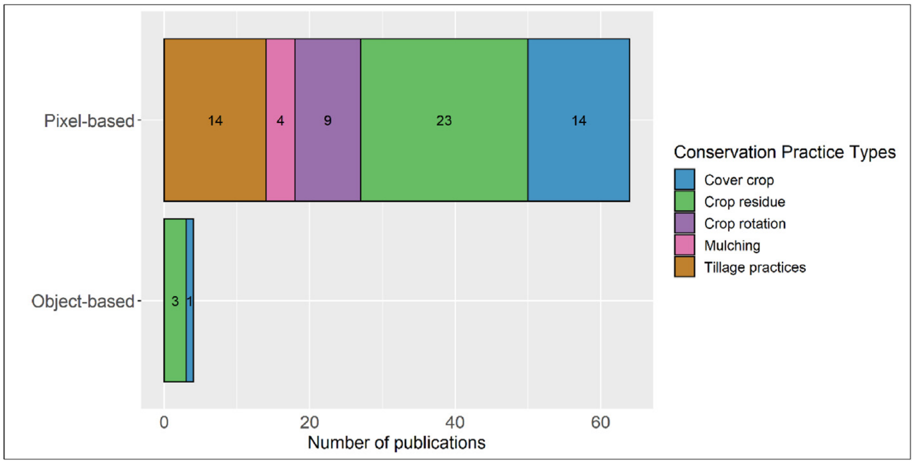

Fig. 4. Conservation practices and classification methods from 1991 to 2021.

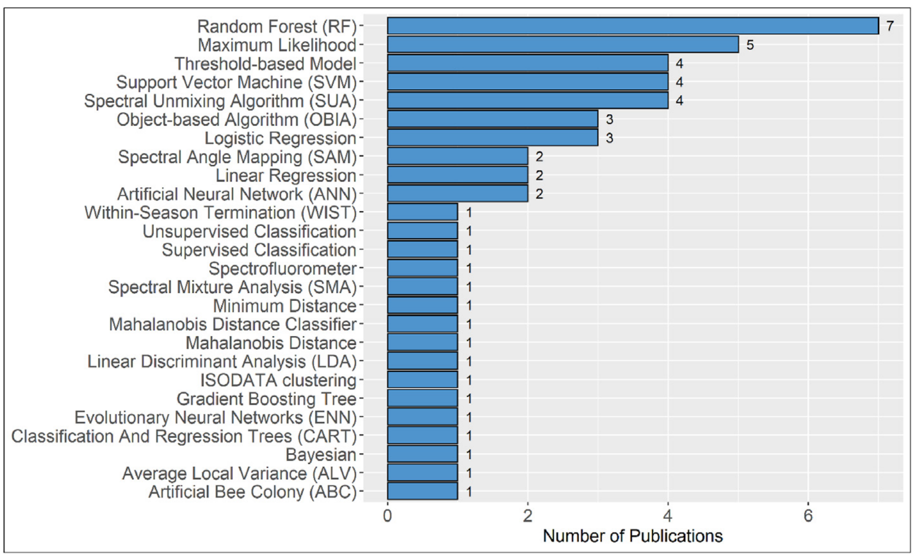

Fig. 5. Conservation agriculture papers by classification algorithm types from 1991 to 2021.

algorithms used, the Random Forest and Maximum Likelihood were used the most (13% and 10% of the publications, respectively). Additionally, 23% of articles integrated the usage of a Support Vector Machine, Spectral Unmixing Algorithm, or Threshold-based models. The remaining papers (54%) combined used the other classification algorithms.

4.6. Conservation agriculture and classification algorithm

Image classification using various classification algorithms has gained traction in recent years due to the development of new tools, techniques, and algorithms. As many machine learning and classification algorithms have developed, such as the Random Forest (RF), Gradient Boosting Tree, Support Vector Machine (SVM), Classification and Regression Trees (CART), and other methods, classification accuracy has improved. These algorithms are freely available and widely used in conservation agriculture research. Fig. 6 shows all the classification algorithms and conservation practices used by the studies identified for the current examination. Among the various algorithms, only Random Forest was used by all of the conservation practices. Additionally, crop rotation, tillage practices, and crop residue conservation practice all used the Maximum Likelihood approach.

4.7. Conservation agriculture papers citations by years grouped by classification algorithm type

The classification algorithm type has a large number of levels. To avoid clutter, the top six algorithm types represented 68% of the total citations, with their use trend shown in Fig. 7. Overall, the logistic regression classification algorithm had the largest number of citations. The Random Forest algorithm gained recent popularity compared to the other algorithms, among which Spectral Angle Mapping was the next most frequently used.

4.8. Classification algorithm types and accuracy

Table 3 shows various classification algorithms and their accuracies used in the selected papers. From the 52 articles that stated employing one or more classification algorithm types, only 26 papers (38%) demonstrated accuracy using 15 classification algorithm types. As can be seen from Table 3, modern classification

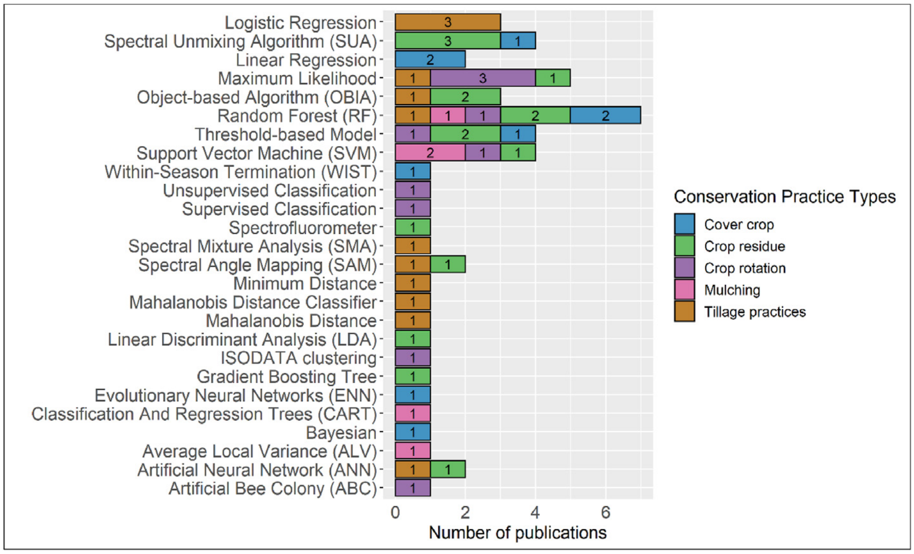

Fig. 6. Conservation practices and classification algorithm from 1991 to 2021.

algorithms, like Evolutionary Neural Networks (ENN), Gradient Boosting Tree, Classification and Regression Trees (CART), Random Forest (RF), and Object-based Algorithm (OBIA) generally outperformed older algorithms for identifying conservation practices. Except for Spectral Unmixing Algorithm (SUA) and Artificial Neural Network (ANN), the majority of classification algorithms' mean accuracy was to be greater than 80%.

4.9. Number of conservation agriculture papers and conservation practice types

Various types of conservation practices have been used in conservation agriculture studies. Among the 68 articles, three studies reported using more than one conservation practice. Thirty-eight percent of the studies used crop residue, which was followed by tillage practices (23%), cover crop (20%), crop rotation (13%), and mulching (6%).

4.10. Conservation agriculture papers citations by years grouped by conservation practice type

The yearly trends of conservation agriculture research by conservation practice type reveal that citations for tillage practice were high early on, with less reference to tillage practice after 2005 (Fig. 8). From 2004 to 2012, crop residue was highly cited, whereas the focus shifted to cover crops from 2012 to 2020, with no citations before 2007 on cover crops.

4.11. Conservation agriculture papers and data type

Different remote sensing data products have been used in conservation agriculture research. Among them, optical and radar data were common and frequently used in several studies. Some studies used single-data types, while other studies used a combination of both optical and radar data. Of these two data types, 62

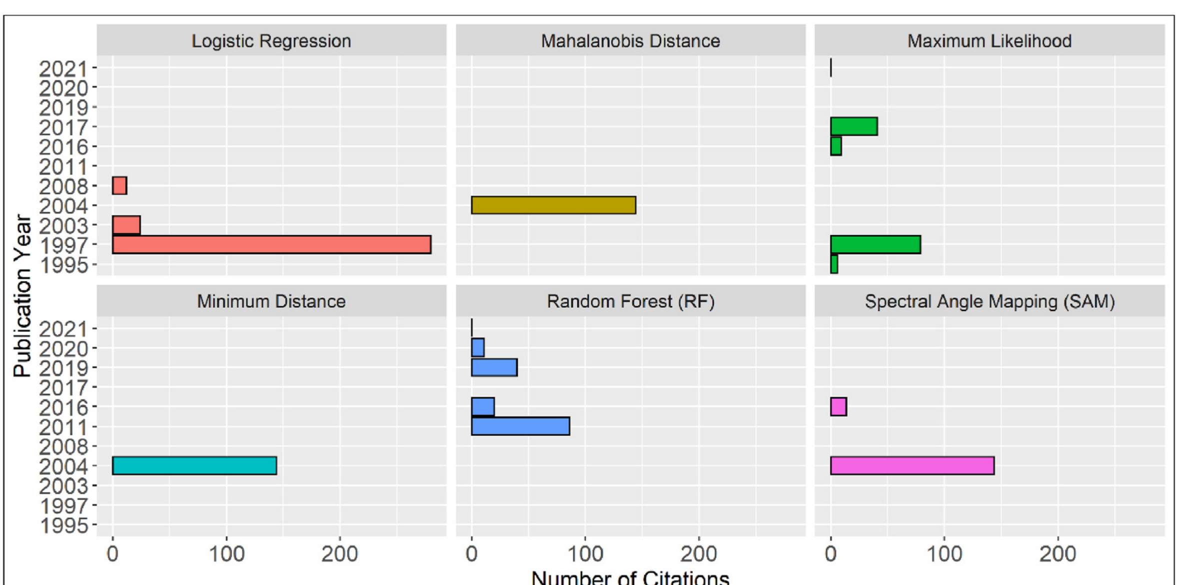

Fig. 7. Conservation agriculture papers citations by years grouped by classification algorithm type from 1991 to 2021.

Table 3
Classification algorithm types and accuracy.

Classification algorithm type	Mean accuracy (%)	Accuracy range (%)	Number of articles
Evolutionary Neural Networks (ENN)	98	–	1
Gradient Boosting Tree	93	–	1
Classification and Regression Trees (CART)	92	–	1
Logistic Regression	90	88–93	2
Object-based Algorithm (OBIA)	86	74–92	3
Random Forest (RF)	86	75–95	6
Spectral Angle Mapping (SAM)	86	76–96	2
Artificial Bee Colony (ABC)	86	–	1
Mahalanobis Distance Classifier	85	–	1
Supervised Classification	85	–	1
Threshold-based Model	84	–	1
Maximum Likelihood	83	73–93	3
Support Vector Machine (SVM)	81	75–86	3
Artificial Neural Network (ANN)	73	–	1
Spectral Unmixing Algorithm (SUA)	65	–	1

[Note: Mean accuracy by classification algorithm types from 1991 to 2021].

studies used the single optical data type, while only one used radar data type. Five studies used both optical and radar data.

4.12. Conservation agriculture and sensor type, number of bands, and spatial resolution

In conservation agriculture studies, 19 types of satellites and sensors were used to identify different conservation practices (Fig. 9). The Landsat 7 satellite was the leading source, followed by earlier and later releases. Landsat 7 was launched in 1999, and Landsat 8 was launched in 2013. To identify mulching, the Gaofen-1 satellite had more citations than Landsat 5. Landsat 7 and UAV were used in most articles (combined 5%) when attempting to identify cover crops, with Landsat 5, 8, and Sentinel 2 also used in many papers (combined 4%). For the identification of cover crops, the least used common satellites were SPOT and Probe-1.

Different spatial resolution imagery was classified into three groups: high (more than 0 and less than 10 m), medium (greater than or equal to 10 to less than or equal to 30 m), and low (greater than 30 to less than or equal to 1000 m) (Fig. 10). The satellites within the medium-resolution group were used in most articles (31%) for all conservation practices. To identify conservation practices of cover crops, crop residue, crop rotations, mulching, and tillage practices, medium spatial resolution imagery was used most. The sensors in the lower resolution group were only used in a few articles concerning crop rotation, cover crops, and tillage practice.

Out of the 68 conservation agriculture studies, four bands/features were used in a limited number of studies for cover crops (5 studies), crop rotation (4 studies), and mulching (3 studies) (Fig. 11). However, in crop residue and tillage studies, most articles (17.5%) stated using three bands/features. The use of sensors above nine bands was the least common among the selected studies (9.5%).

4.13. Conservation agriculture and spectral indices

Among the conservation agriculture studies used in this examination, 31 spectral indices were reported. There were ten indices that were used in most (76%) of the 68 studies (Fig. 12). The Normalized Difference Vegetation Index (NDVI) was reported in 29 studies, followed by the Normalized Difference Tillage Index (NDTI) and the Cellulose Absorption Index (CAI) in 15 and 11 studies, respectively. The remaining indices were reported in four or fewer studies.

NDVI indices were the most common (30%) for different conservation practices and the leading tool to identify cover crops. For crop residue, the CAI index had the largest number of articles. The NDTI was not used most frequently to identify tillage practices (Fig. 13). Also, NDVI was used to identify the largest number of different practices.

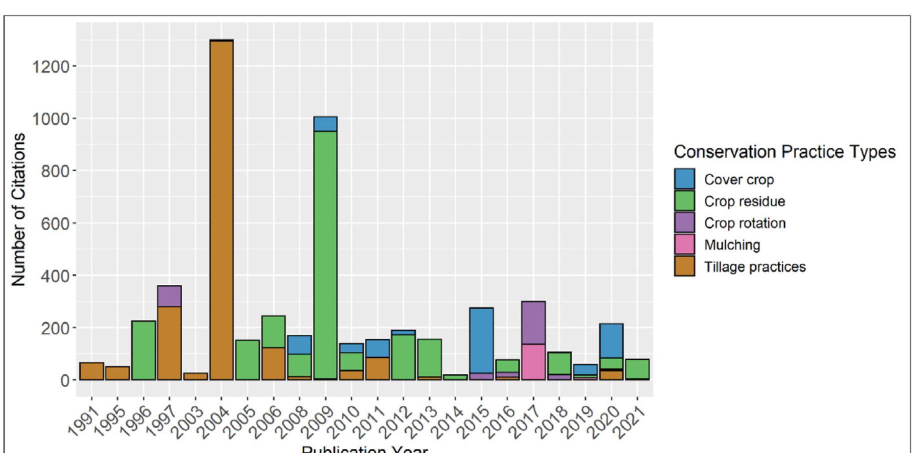

Fig. 8. Conservation agriculture papers citations by years grouped by conservation practice type from 1991 to 2021.

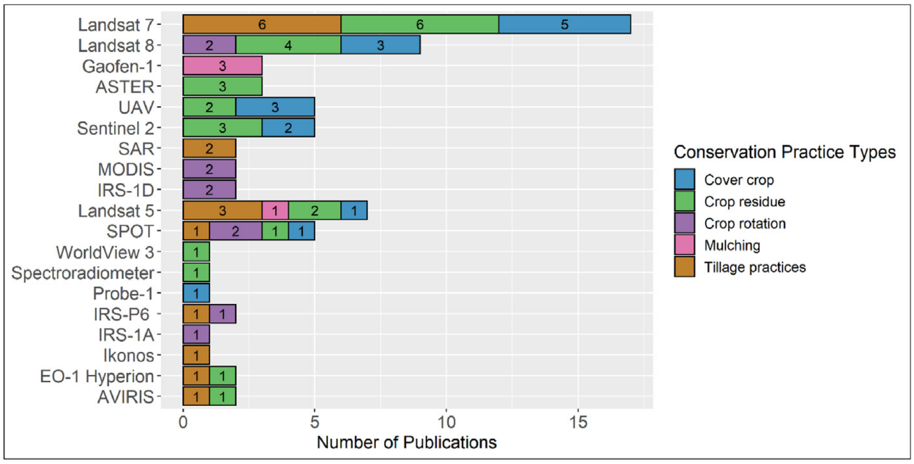

Fig. 9. Conservation agriculture and sensor/satellite type from 1991 to 2021.
[ASTER: Advanced Spaceborne Thermal Emission and Reflection Radiometer; UAV: Unoccupied Aerial Vehicle; IRS: Indian Remote Sensing; SPOT: Satellite Pour l'Observation de la Terre; SAR: Synthetic Aperture Radar; MODIS: Moderate Resolution Imaging Spectroradiometer; EO-1: Earth Observing-1; AVIRIS: Airborne Visible/Infrared Imaging Spectrometer].

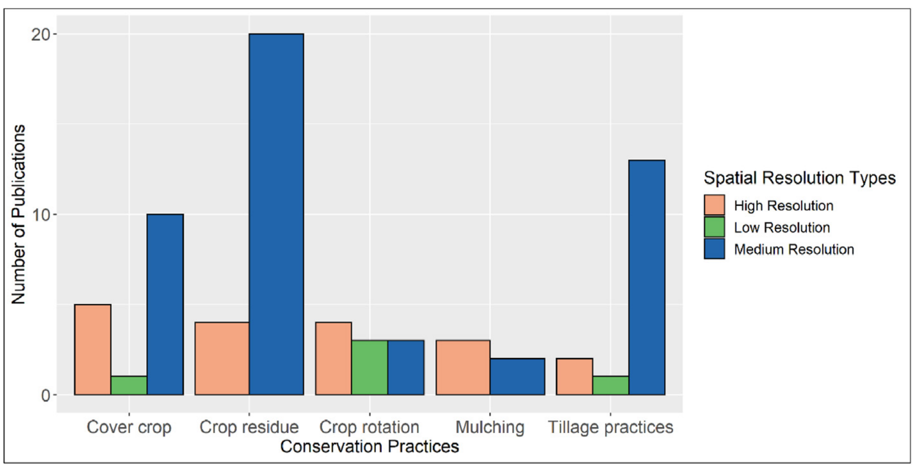

Fig. 10. Conservation agriculture and spatial resolution by practice from 1991 to 2021. [Note: Spatial resolution (pixel size in meters along one dimension): High: > 0 to < 10; Medium: ≥ 10 to ≤ 30; Low: > 30 to ≤ 1000].

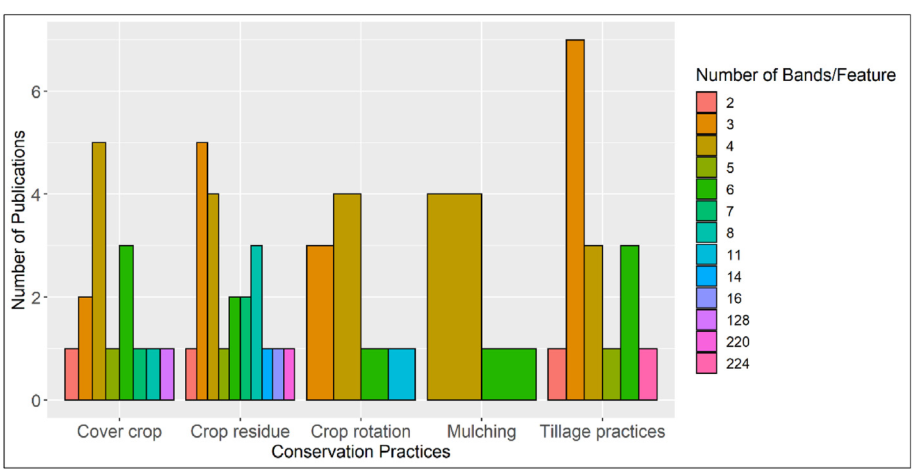

Fig. 11. The number of bands used by conservation agriculture practices from 1991 to 2021.

4.14. Conservation agriculture practices and crop species

Fig. 14 indicates that maize (*Zea mays*) has been a part of all conservation practices analyzed in this examination. Likewise, soybeans (*Glycine max*) have also been part of all the practices except for mulching. Mulching was only reported for a maize crop in 2 out of 68 articles.

5. Discussion

There has been an increasing number of papers targeting the identification of conservation practices using remote sensing published since 1990 with the annual trend increasing. This was expected given that new remote sensing technologies have developed and been more precise over time (Crowley & Cardille, 2020). There may be other factors at play, but the fact that the number of research publications on remote sensing in conservation agriculture has doubled in the last decade suggests that, due to the most recent technologies such as sensors, satellites, and algorithms, as well as the availability of data and ease of data transmission, research on agricultural conservative practices using remote sensing is becoming more funded, more studied, or both (Rogan & Chen, 2004).

Remote sensing devices are based on several categories, including airborne, satellite, or ground-based platforms (Cracknell, 2018). Satellites, drones, helicopters, and aircraft are a few types of aerial remote-sensing equipment. To gather data, these devices frequently have sensors like cameras, lidar, radar, and other sorts of sensors. There are several uses for airborne optical remote sensing, including mapping, surveying, and environmental monitoring. In conservation agriculture studies, researchers have used mostly optical data during their research using remote sensing platforms (Aoki et al., 2021; Brooker et al., 2021; Chi & Crawford, 2014; Galloza et al., 2013; Gelder et al., 2009; Jayanth et al., 2021; Maas & Rajan, 2008; Nowak et al., 2021; Obade & Gaya, 2020; Seifert et al., 2019; Sood et al., 2009).

Although radar technology has existed for over five decades, radar has not been as widely utilized as optical remote sensing (Rogan & Chen, 2004). There have not been many active radar applications for conservation agriculture research, despite the theory supporting their usefulness in various areas, such as natural environments (Kasischke et al., 1997). This might be attributable to inadequate techniques for radar data analysis and a general lack of comprehension of radar data. It has been observed that satellite remote sensing information has been used often for conservation agricultural research. One explanation might be that the researchers are more accustomed to and at ease using optical data than radar data. Additionally, the price of satellite data might also have an impact. Some satellite data is freely available to the public when using Landsat, Sentinel, and MODIS. Additionally, the availability of geometrically corrected optical data, a wider perspective of the land, less preparation of images, more preprocessing software, and less trained expertise are all contributing factors. In the current examination, only one study used radar data (Brisco et al., 1991), with other studies using a combination of both optical and radar in their publications (Hasituya, Chen, Li, & Hongmei, 2017, 2020; Leek & Solberg, 1995; Smith et al., 1995; Sood et al., 2009). The potential of radar in natural environments seems to be more understood by the remote sensing research community, although work on conservation agriculture is still ongoing, particularly about the synergistic use of optical and radar data (Gamba & Houshmand, 2010; Hasituya, Chen, Li, & Hongmei, 2017, 2020).

Among the optical data, Landsat 7 and Landsat 8 platforms were popular in crop residue (Barnes et al., 2021; Chi & Crawford, 2014; Laamrani et al., 2020; Najafi et al., 2018; Pacheco & McNairn, 2010; Sonmez & Slater, 2016; Zheng et al., 2012, 2013b), tillage practices (Gowda et al., 2008; Hagen et al., 2020; South et al., 2004; Sudheer et al., 2010; Watts et al., 2011; Zheng, Campbell, Shao, & Wynne, 2013), and cover crop (Hively et al., 2015, 2020; Seifert et al., 2019; Thieme et al., 2020; Xu et al., 2018) conservation practices. In contrast, Landsat-5 and the Gaofen-1 platforms were popular in mulching conservation practice (Hasituya, Chen, Li, & Hongmei, 2017, 2017b, 2020; Xiong et al., 2019), while fewer studies used UAVs (Brooker et al., 2021; Cruz-Ramírez et al., 2012; Hunt et al., 2011; Yue & Tian, 2020) for cover crop and crop residue conservation practices. According to the literature summarized in this study, the UAVs have not been widely used in conservation agriculture. Although UAVs have a high spatial resolution, they are expensive and have low coverage. The UAVs are beneficial when the area covered is small. As such, UAVs are primarily used in precision agriculture applications (Delavarpour et al., 2021). Overall, results showed that researchers are more inclined to use old remote sensing technologies rather than proposing or using new tools and techniques. However, in recent years, the trend of using new

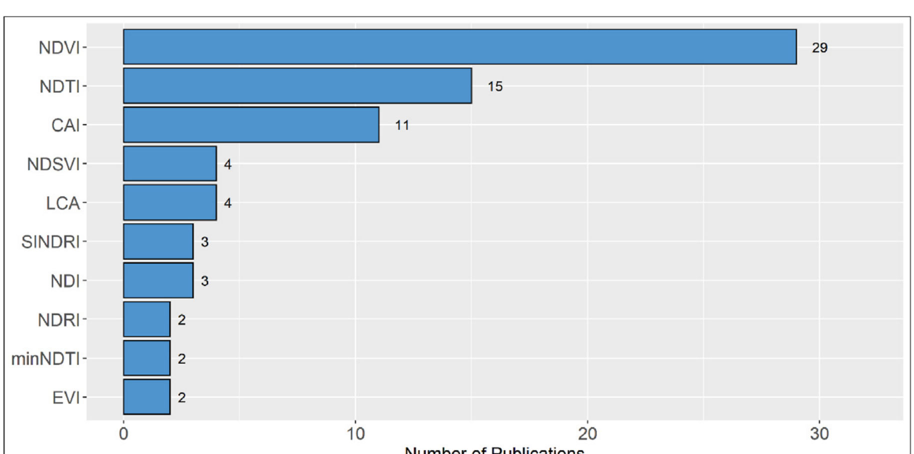

Fig. 12. Top 10 indices found in conservation agriculture publications from 1991 to 2021. [Note: NDVI: Normalized Difference Vegetation Index; NDTI: Normalized Difference Tillage Index; CAI: Cellulose Absorption Index; NDSVI: Normalized Difference Senescent Vegetation Index; LCA: Lignin-Cellulose Absorption Index; SINDRI: Shortwave Infrared Normalized Difference Residue Index; NDI: Normalized Difference Index; NDRI: Normalized Difference Residue Index; minNDTI: Minimum values of Normalized Difference Tillage Index; EVI: Enhanced Vegetation Index].

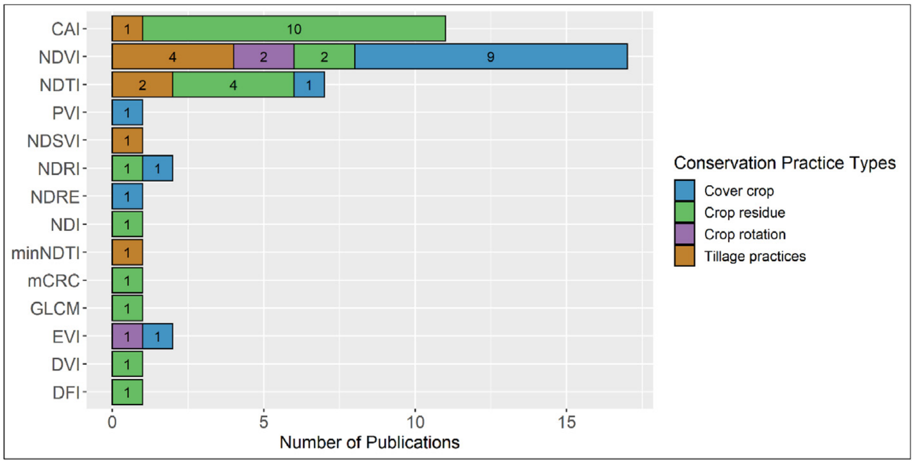

Fig. 13. Top 10 indices grouped by conservation practices from 1991 to 2021.

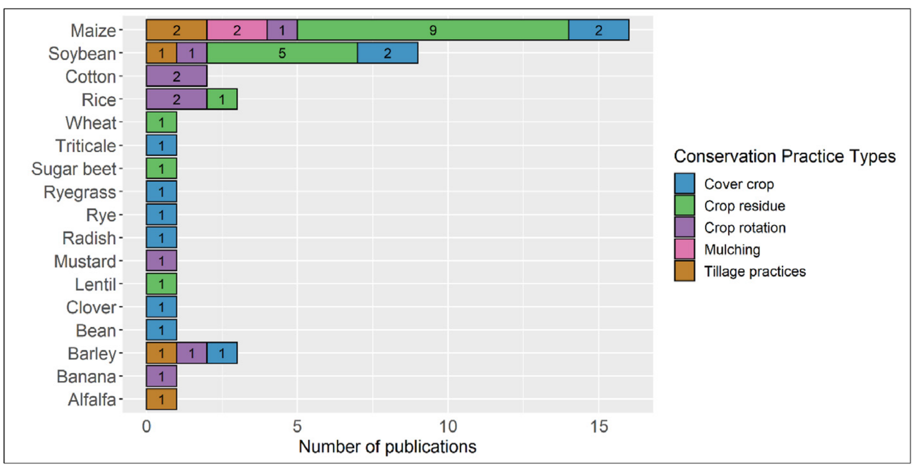

Fig. 14. Conservation practices and crop types from 1991 to 2021.

remote sensing tools and techniques has been increasing (Crowley & Cardille, 2020).

Satellite systems with increasing spatial resolution have proliferated over the past few years. The constantly growing constellation of satellite platforms has gathered trillions of bytes worth of data that will be useful for conservation agricultural research. The spatial resolution is important for any research on satellite images (Fisher et al., 2018). The greater the spatial resolution, the greater the image quality, and the greater the accuracy in correctly identifying objects in the image (Wulder et al., 2004; Zhou et al., 2018). Results suggest that almost all conservation practice categories used medium (Beeson et al., 2020; Daughtry et al., 2003; Galloza et al., 2013; Hagen et al., 2020; Hively et al., 2019; Kc et al., 2021; Leek & Solberg, 1995; Nowak et al., 2021; Serbin et al., 2009a, 2009b, 2009c; Thieme et al., 2020; Xiong et al., 2019) to high spatial resolution images (Beeson et al., 2016; Brooker et al., 2021; Cruz-Ramírez et al., 2012; Galloza et al., 2013; Jayanth et al., 2021; Koger et al., 2004; Najafi et al., 2021; Pacheco et al., 2008; Panigrahy & Sharma, 1997; Viña et al., 2003; Waldhoff et al., 2017; Yue & Tian, 2020) in their articles and only a few studies used low spatial resolution images (Conrad et al., 2016; Hively et al., 2009; Liu et al., 2018; Obade & Gaya, 2020; Watts et al., 2011; Xiong et al., 2019). It is important to note that many studies used combinations of high, medium, and low spatial resolution images. However, the medium spatial resolution group was used in most articles, especially in crop residue (Beeson et al., 2016; Chi & Crawford, 2014; Daughtry et al., 2005; Dvorakova et al., 2020; Galloza et al., 2013; Gelder et al., 2009; Hively et al., 2019; Najafi et al., 2018; Serbin et al., 2009a, 2009b, 2009c; Zheng et al., 2012), tillage practice (Beeson et al., 2020; Gowda et al., 2008; Hagen et al., 2020; Leek & Solberg, 1995; Sonmez & Slater, 2016; Sudheer et al., 2010; Watts et al., 2011; Zheng, Campbell, Shao, & Wynne, 2013), and cover crop (Gao et al., 2020; Hively et al., 2015, 2020; Hunt et al., 2011; Kc et al., 2021; Seifert et al., 2019; Thieme et al., 2020; Yue & Tian, 2020) conservation practice identification studies. It is anticipated that medium spatial resolution data will continue to contribute into the future (Franklin, 2001). One reason for this is that data from some satellite images are freely available. The sensors of low-resolution groups were used in a few articles regarding crop rotation (Conrad et al., 2016), cover crop (Hively et al., 2009), and tillage conservation practices (Obade & Gaya, 2020). Basic land-cover and land-use data have long been acquired using low-resolution images of large areas. In contrast, high-to-medium resolution optical data-collecting technologies have developed quickly lately. As a result, a wide range of spatial, spectral, and temporal resolutions from remote sensing data have been used in conservation agriculture studies.

In terms of bands and/or features, the phrases multispectral and hyperspectral images are similarly related. These classifications are based on the number of recorded bands rather than specific wavelengths. Multispectral images are ones in which just a few bands, often three to 10 bands, are captured for each pixel (García-Berná et al., 2020). Each band represents a sizeable fraction of the spectrum, and each band may be given an illustrative name. A Red, Green, and Blue (RGB) image, for instance, may be considered as a three-band multispectral image. However, not all of the 11 unique bands that the Lansat-8 satellite can capture have the same level of spatial resolution. The many bands in hyperspectral images, which can number hundreds or even thousands, make them distinctive (García-Berná et al., 2020). The Hyperion imaging spectrometer, for instance, can capture 224 bands at intervals of 10 nm in wavelength (Pearlman et al., 2001). This enormous number of bands enables a precise and detailed analysis of the observed items by acquiring the spectral signature of the conservation practices being investigated. The majority of machine learning approaches, however, were created for images with a fixed number of bands. When the images have a low spatial resolution but a large band count, specific techniques should be used. Most of the agricultural conservation practices selected in this study used three to four bands. Red, Green, Blue, and Near Infrared (NIR) bands were the most frequently used image bands. Red, Green, and Blue (RGB) helps with a simple inspection of results when it comes to agricultural practices, but they are of little help in discriminating crop cover and residue as the class category is almost the same in the context of land use and vegetation. However, NIR helps identify a crop or object due to its reflectance property of the wavelength in the vegetation class. Near Infrared is also beneficial for differentiating between different objects of interest. From the results, five studies (Gao et al., 2020; Hively et al., 2009, 2015, 2020; Prabhakara et al., 2015), four studies (Conrad et al., 2016; Liu et al., 2018; Manjunath et al., 2015; Waldhoff et al., 2017) and three studies (Hasituya, Chen, Li, & Hongmei, 2017, 2020; Xiong et al., 2019) reported the use of four bands in cover crop, crop rotation, and mulching, respectively. However, in crop residues (Barnes et al., 2021; Chi & Crawford, 2014; Dvorakova et al., 2020; Serbin et al., 2009c; Sonmez & Slater, 2016) and tillage conservation studies (Beeson et al., 2020; Brisco et al., 1991; Gowda et al., 2008; Hagen et al., 2020; Smith et al., 1995; Zheng, Campbell, Shao, & Wynne, 2013), most of the articles stated the use of three bands. Only a few studies have used more than nine bands (Chi & Crawford, 2014; Daughtry et al., 2003; Daughtry & Hunt, 2008; Galloza et al., 2013; Hively et al., 2018; Pacheco et al., 2008; Serbin et al., 2009a, 2009b; Zhao et al., 2012). A large spatial resolution hyperspectral band image is helpful in identifying and getting detailed information about an object or crop.

The image classification problem may be regarded from the perspectives of classification units and classification features to compare the differences between object and pixel-based classification techniques (Liu & Xia, 2010). In pixel-based classification, mathematical calculations are applied based on the spectral bands of the image. For example, for crop rotation, NDVI is calculated by combining Landsat near-infrared (band 4 of Landsat 5–7 or band 5 of Landsat 8) and red (band 3 of Landsat 5–7 or band 4 of Landsat 8) bands. The pixel-based classification would give the result in the form of pixels. Pixel-based classification (Beeson et al., 2016, 2020; Hagen et al., 2020; Hively et al., 2018; Hunt et al., 2011; Muñoz et al., 2010; Obade & Gaya, 2020; Seifert et al., 2019; South et al., 2004; Sudheer et al., 2010; Thieme et al., 2020; Van Deventer et al., 1997; Viña et al., 2003) was the principal classification approach adopted in most of the research papers. The pixel-based classification method was mostly adopted for the identification of crop residue (Barnes et al., 2021; Beeson et al., 2016; Hively et al., 2018), cover crop (Hively et al., 2015; Kc et al., 2021; Seifert et al., 2019; Thieme et al., 2020) and tillage practice (Beeson et al., 2020; Gowda et al., 2008; Leek & Solberg, 1995; Watts et al., 2011) in comparison to crop rotation (Conrad et al., 2016; Jayanth et al., 2021; Panigrahy & Sharma, 1997) and mulching conservation practices (Hasituya, Chen, Li, & Hongmei, 2017, 2020; Xiong et al., 2019). The information suggests that researchers are finding it easier to use pixel-based classification because it is less difficult in terms of local knowledge, cost, and resources than object-based classification. However, comparing pixel accuracy to object-based classification, a newly developed method (Cruz-Ramírez et al., 2012; Najafi et al., 2018, 2021), object-based produced better accuracy. In object-based classification, RGB components are extracted in the classification technique from the images. The object-based method is followed by image segmentation after preprocessing the images, i.e., balancing of color transformation and processing. The object-based technique outperforms the pixel-based strategy in these two instances. First, moving from object to pixel-based classification reduces within-class spectral variation and, in most cases, removes the so-called salt-and-pepper effects. In order to possibly improve classification accuracy, a large variety of attributes that define the spatial, textural, and contextual aspects of objects may be inferred in addition to the direct spectral observations (Guo et al., 2007). The object-based method, in contrast, has its own drawbacks about the two characteristics. Over and under-segmentation are two common forms of segmentation mistakes in object-based classification methods (Möller et al., 2007). Because all pixels in each mixed image object must be assigned to the same class, under-segmentation results in image objects that cover more than one class, which introduces classification errors. Additionally, features extracted from mis-segmented image objects with over or under-segmentation errors do not accurately represent the characteristics of real objects on the Earth's surface (Song et al., 2011). As a result, the use of images objects as classification units and the inclusion of the objects' characteristics in classification have both positive and negative implications on the ultimate performance of object over pixel-based classification methods. When using object-based classification techniques, care must be taken to choose the correct segmentation scale (Liu & Xia, 2010). Furthermore, in a few articles, some researchers have used rule-based classification techniques (Liu et al., 2018) along with pixel and object-based classification. Rule-based is the conventional technique to find out the reflectance of the images based on formulae and is useful when combined with other methods and when local knowledge and ground data are limited (Lu & Weng, 2007).

Early 1990s conservation agriculture studies using remote sensing techniques relied heavily on supervised methodologies like Logistic Regression (Van Deventer et al., 1997), Maximum Likelihood (Leek & Solberg, 1995; Panigrahy & Sharma, 1997) as well as various types of reflectance/spectral-based methods (Brisco et al., 1991; Daughtry et al., 1996; Smith et al., 1995). The reliance on supervised methodologies is primarily attributable to the fact that the supervised classifiers and/or methods were widely used at the time (Lu & Weng, 2007). The following generation of classifiers used in conservation agriculture studies using remote sensing techniques between 2000 and 2010 included the Spectral Unmixing Algorithm (Pacheco et al., 2008; Pacheco & McNairn, 2010), Spectral Angle Mapping (South et al., 2004), Bayesian (Muñoz et al., 2010), among a few other algorithms. Recent studies after 2010 examined the well-known classification algorithms as well as older generation classification algorithms used in conservation agriculture studies using remote sensing techniques, including Random Forest (Barnes et al., 2021; Conrad et al., 2016; Hasituya et al., 2020; Kc et al., 2021; Seifert et al., 2019; Watts et al., 2011; Yue & Tian, 2020), Gradient Boosting Tree (Hively et al., 2019), Support Vector Machine (Hasituya, Chen, Li, & Hongmei, 2017, 2017b; Najafi et al., 2021; Waldhoff et al., 2017), Object-based Algorithm (Najafi et al., 2018, 2021; Zheng, Campbell, Shao, & Wynne, 2013), Artificial Neural Network (Najafi et al., 2021), Evolutionary Neural Networks (Cruz-Ramírez et al., 2012), Classification and Regression Trees (Xiong et al., 2019), among a few others. These classifiers do not require normally distributed input data since most are non-parametric (Mahdianpari et al., 2020). This is especially helpful when several input data sources are used in the classification scheme to increase classification accuracy, such as spectral, geometrical, textural, and vegetation indices. Significant improvements were later observed when object-based classification was combined with spectral, spatial, and contextual information (Najafi et al., 2018, 2021; Zheng, Campbell, Shao, & Wynne, 2013). New studies evaluated how various types of neural networks used in remote sensing, particularly deep- and machine-learning models, may increase the accuracy of classifying conservation methods (Cruz-Ramírez et al., 2012; Najafi et al., 2021). In conservation agriculture using remote sensing, the use of the newest machine- and deep-learning algorithms is still relatively low. One of the primary reasons is that these techniques demand advanced software expertise and domain understanding. Various classification algorithms and conservation techniques employed by multiple studies are presented in a comprehensive manner, along with conservation publications cited by different types of classification algorithms and various classification algorithms and their accuracy. As can be seen, among other classification techniques for conservation agriculture using remote sensing research, Random Forest, Maximum Likelihood, Logistic Regression, Support Vector Machine, Gradient Boosting Tree, and Object-based Algorithm (OBIA) received more attention. The supervised machine learning algorithms mentioned above are used in conservation agriculture research for a variety of reasons, including their ability to model relationships and dependencies between input characteristics and the intended prediction output, which enables researchers to forecast the values of the output for brand-new data using the relationships that the algorithms have learned from previous data sets. For example, in the case of the Random Forest algorithm, on various samples, it constructs decision trees and uses their average for classification and majority vote for regression modeling. One of the most important features of the Random Forest Algorithm is its capacity to handle data sets, including both continuous variables, as in regression, and categorical variables, as in classification. The Random Forest algorithm has evolved into a common classification technique that competes with Logistic Regression in several research on conservation agriculture. Logistic regression is recognized as a common strategy and is frequently used in conservation agriculture to address binary classification problems when dealing with low-dimensional data or when the number of variables is modest relative to the sample size. Due to improvements in multiple algorithmic approaches and enhanced classification algorithms, accuracy has significantly increased in recent years.

Combinations of spectral reflectance from two or more wavelengths are known as spectral indices, and they may be used to calculate the relative abundance of specific characteristics of interest. Although vegetation is the most prevalent type of indicator, there are other indices for burnt regions, man-made features, water, and geologic features. The NDVI index is most typically used to assess different crops and plants' health, developmental phases, biomass, and yield expectations. The NDVI has surpassed other vegetation indices in terms of usage (Wallace et al., 2004). Other indices are mostly crop- and/or conservation-practice specific. To optimize the crop residue signal and the partial cover of agricultural residue, quantitative techniques primarily use various regression techniques using spectral indices (Zheng et al., 2014). The most common tillage indices are the Cellulose Absorption Index (CAI) (Van Deventer et al., 1997) and the Normalized Difference Tillage Index (NDTI) (Daughtry et al., 2005). However, environmental factors like soil moisture or residual water content have an impact on the outcomes. The NDVI (Barnes et al., 2021; Hively et al., 2009, 2020; Kc et al., 2021; Obade & Gaya, 2020; Seifert et al., 2019; Viña et al., 2003) was shown to be the most promising index for identifying agricultural conservation practices followed by the NDTI (Beeson et al., 2020; Daughtry et al., 2005; Serbin et al., 2009a; Yue & Tian, 2020; Zheng et al., 2012) and the CAI (Dvorakova et al., 2020; Zheng, Campbell, Serbin, & Daughtry, 2013) that was applied in the identification of cover crops, crop residue, crop rotation, and tillage practices. With the advent of technology and data transmission facilities, NDVI is increasingly used, whereas others have also been upward trending over time but more sporadically. Numerous efforts have been undertaken to create new indices that might lessen the influence of the soil background and atmospheric effects on the outcomes of spectral observations.

Most of the conservation practice groups used maize as a crop of interest. At the same time, soybean has been part of all the practices except for mulching. Rice and maize were also important crops for the conservation practice groups because, especially in the U.S., Canada, China, and India, farmers cultivate these crops more than others. The sole purpose of this part of the analysis was to show the types of crops being used in remote sensing-based conservation agriculture research. However, some crops could have been sensed or analyzed using remote sensing methods, while others may not have been sensed or analyzed using remote sensing methods but used in those articles. In summary, care must be used when interpreting results because this study did not distinguish between crops that were sensed and those that were not using remote sensing techniques.

Study limitations

Every systematic review has limitations. The current examination has several possible limitations, including.

1) Using different key concepts and associated keywords search strings can result in entirely different types and number of articles. As this research focus was to identify different remote sensing tools and techniques that have been used in conservation agriculture research, some pre-listed general conservation practices and remote sensing keywords were used to reduce this limitation by forming search strings as broadly as possible. Trial and error led to several related articles deemed appropriate to elicit trends in application techniques used over time.
2) The inclusion criteria of selecting only English articles could have rejected some relevant papers that could have impacted the results, specifically in non-English speaking countries.
3) The inclusion criteria of selecting only peer-reviewed research articles and excluding review articles, conference proceeding papers, data papers, book chapters, letters, editorial materials, and grey literature could have rejected some relevant papers that could have impacted the results. When searching for papers in the databases, there were no restrictions on publication years, yet the results eventually included works dating back to 1991. Therefore, publications from 1991 to 2021 were assumed to have provided representative results.
4) The current study purposely did not focus on biophysical remote sensing models to quantitatively estimate important variables, such as plant biomass and soil moisture, since they have already been well studied in previous literature reviews, thus were beyond the intended scope of this study, while the categorical/

thematic nature of the current examination was the focus due to the lack of literature attention on this aspect.

6. Summary and conclusions

Remote sensing-based conservation agriculture research has long attracted the interest of both the agricultural and remote sensing communities. This popularity is because of the effectiveness of its tools and methods in providing detailed information for the field as well as the foundation for numerous environmental and socioeconomic applications. Researchers and scientists have created advanced remote sensing technologies and procedures to improve the identification, categorization, and accuracy of diverse domains, including conservation agricultural practices. The heterogeneity of the land area, the availability of cloud-free remotely sensed optical data, the level of technical and software expertise required to process a large number of satellite imageries, and, most importantly, the types of tools and techniques used may all have an impact on the success of conservation agriculture research using remote sensing. As a result, identifying and classifying satellite imagery and turning them into actionable data and insights for conservation agriculture research remains a challenge.

Over the past few decades, remote sensing has improved significantly, particularly in developing different machine- and deep-learning algorithms and using cutting-edge tools and techniques. As a result, starting in the early 1990s, there has been a progressive rise in publications related to conservation agriculture using remote sensing methods. Remote sensing technology can help many conservation agriculture practices for which there is insufficient information. Optical data from Landsat, Sentinel, and other satellites and UAVs are presently used by the majority of conservation agriculture researchers. There are many more opportunities to use radar data, which can sense through clouds, but requires enhanced expertise.

Regarding various remote sensing technologies, the current examination has provided a snapshot of many forms of agricultural conservation methods. The results of individual research could not be summed up since we dealt with and examined various conservation practices using various satellite data, methodologies, and algorithms. However, the qualitative analysis sheds light on the common remote sensing tools, methods, and algorithms used to identify five important agricultural conservation practices. The results of this study, which represent a relatively comprehensive examination of remote sensing for conservation agriculture, will be helpful to scholars of conservation as well as other researchers and policymakers who are interested in conservation research both domestically and internationally. Furthermore, this study used a systematic process for assessing and evaluating remote sensing techniques to date and provided insights about potential future applications in conservation agriculture research.

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Declarations

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

CRediT authorship contribution statement

Zobaer Ahmed: Conceptualization, Methodology, Software, Writing – original draft, Data curation, Formal analysis, Visualization, Investigation, Writing – review & editing. **Aaron Shew:** Conceptualization, Validation, Supervision, Resources, Writing – review & editing. **Lawton Nalley:** Validation, Supervision, Resources, Writing – review & editing. **Michael Popp:** Validation, Supervision, Resources, Writing – review & editing. **V. Steven Green:** Validation, Supervision, Resources, Writing – review & editing. **Kristofor Brye:** Validation, Supervision, Resources, Writing – review & editing.

References

Aboutalebi, M., Allen, N., Torres-Rua, A. F., McKee, M., & Coopmans, C. (2019). Estimation of soil moisture at different soil levels using machine learning techniques and unmanned aerial vehicle (UAV) multispectral imagery. In *Autonomous air and ground sensing systems for agricultural optimization and phenotyping IV; 110080S* (p. 26). SPIE-Intl Soc Optical Eng. https://doi.org/10.1117/12.2519743.

Adão, T., Hruška, J., Pádua, L., Bessa, J., Peres, E., Morais, R., & Sousa, J. J. (2017). Hyperspectral imaging: A review on UAV-based sensors, data processing and applications for agriculture and forestry. *Remote Sensing, 9*. https://doi.org/10.3390/rs9111110

Adu, M. O., Yawson, D. O., Armah, F. A., Abano, E. E., & Quansah, R. (2018). Systematic review of the effects of agricultural interventions on food security in northern Ghana. *PLoS One, 13*. https://doi.org/10.1371/journal.pone.0203605

Ahmad, N. S. B. N., Mustafa, F. B., Yusoff, S. Y. M., & Didams, G. (2020). A systematic review of soil erosion control practices on the agricultural land in Asia. *International Soil and Water Conservation Research, 8*, 103–115. https://doi.org/10.1016/j.iswcr.2020.04.001

Al-Ali, Z. M., Abdullah, M. M., Asadalla, N. B., & Gholoum, M. (2020). A comparative study of remote sensing classification methods for monitoring and assessing desert vegetation using a UAV-based multispectral sensor. *Environmental Monitoring and Assessment, 192*. https://doi.org/10.1007/s10661-020-08330-1

Al-Juboury, I. A. M., & Al-Rubaye, S. A. J. (2021). Integration satellite imagery with fuzzy logic for potential change detection in land use/land cover. In *Journal of physics: Conference series*. IOP Publishing Ltd. https://doi.org/10.1088/1742-6596/1804/1/012036.

Ali, I., Greifeneder, F., Stamenkovic, J., Neumann, M., & Notarnicola, C. (2015). Review of machine learning approaches for biomass and soil moisture retrievals from remote sensing data. *Remote Sensing*. https://doi.org/10.3390/rs71215841

Aoki, A. M., Robledo, J. I., Izaurralde, R. C., & Balzarini, M. G. (2021). Temporal integration of remote-sensing land cover maps to identify crop rotation patterns in a semiarid region of Argentina. *Agronomy Journal, 113*, 3232–3243. https://doi.org/10.1002/agj2.20758

Babaeian, E., Sadeghi, M., Jones, S. B., Montzka, C., Vereecken, H., & Tuller, M. (2019). Ground, proximal, and satellite remote sensing of soil moisture. *Reviews of Geophysics*. https://doi.org/10.1029/2018RG000618

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*. https://doi.org/10.3390/rs13101998

Baumgart-Getz, A., Prokopy, L. S., & Floress, K. (2012). Why farmers adopt best management practice in the United States: A meta-analysis of the adoption literature. *Journal of Environmental Management, 96*, 17–25. https://doi.org/10.1016/j.jenvman.2011.10.006

Beeson, P. C., Daughtry, C. S. T., Hunt, E. R., Akhmedov, B., Sadeghi, A. M., Karlen, D. L., & Tomer, M. D. (2016). Multispectral satellite mapping of crop residue cover and tillage intensity in Iowa. *Journal of Soil and Water Conservation, 71*, 385–395. https://doi.org/10.2489/jswc.71.5.385

Beeson, P. C., Daughtry, C. S. T., & Wallander, S. A. (2020). Estimates of conservation tillage practices using landsat archive. *Remote Sensing, 12*. https://doi.org/10.3390/RS12162665

Belgiu, M., & Csillik, O. (2018). Sentinel-2 cropland mapping using pixel-based and object-based time-weighted dynamic time warping analysis. *Remote Sensing of Environment, 204*, 509–523. https://doi.org/10.1016/j.rse.2017.10.005

Brisco, B., Brown, R. J., Snider, B., Sofko, G. J., Koehler, J. A., & Wacker, A. G. (1991). Tillage effects on the radar backscattering coefficient of grain stubble fields. *International Journal of Remote Sensing, 12*, 2283–2298. https://doi.org/10.1080/01431169108955258

Brooker, A., Renner, K., Price, R. F., & Basso, B. (2021). Evaluating high-resolution

optical and thermal reflectance of maize interseeded with cover crops across spatial scales using remotely sensed imagery. *Agronomy Journal, 113*, 2884–2899. https://doi.org/10.1002/agj2.20592
Brye, K. R., & Pirani, A. L. (2005). *Native soil quality and the effects of tillage in the grand prairie region of eastern Arkansas*. Source: The American Midland Naturalist.
Bullock, D. G. (1992). *Crop rotation, 11* pp. 309–326). CRC Crit Rev Plant Sci. https://doi.org/10.1080/07352689209382349
Burns, B. W., Green, V. S., Hashem, A. A., Massey, J. H., Shew, A. M., Adviento-Borbe, M. A. A., & Milad, M. (2022). Determining nitrogen deficiencies for maize using various remote sensing indices. *Precision Agriculture, 23*, 791–811. https://doi.org/10.1007/S11119-021-09861-4/TABLES/7
Camps-Valls, G., Campos-Taberner, M., Moreno-Martínez, Á., Walther, S., Duveiller, G., Cescatti, A., Mahecha, M. D., Muñoz-Marí, J., García-Haro, F. J., Guanter, L., Jung, M., Gamon, J. A., Reichstein, M., & Running, S. W. (2021). A unified vegetation index for quantifying the terrestrial biosphere. *Science Advances, 7*, 7447–7473.
Candiago, S., Remondino, F., De Giglio, M., Dubbini, M., & Gattelli, M. (2015). Evaluating multispectral images and vegetation indices for precision farming applications from UAV images. *Remote Sensing, 7*, 4026–4047. https://doi.org/10.3390/rs70404026
Chamberlain, L. A., Bolton, M. L., Cox, M. S., Suen, G., Conley, S. P., & Ané, J. M. (2020). Crop rotation, but not cover crops, influenced soil bacterial community composition in a corn-soybean system in southern Wisconsin. *Applied Soil Ecology, 154*. https://doi.org/10.1016/j.apsoil.2020.103603
Chao, H., Baumann, M., Jensens, A., Chen, Y. Q., Cao, Y., Ren, W., & McKee, M. (2008). Band-reconfigurable multi-UAV-based cooperative remote sensing for real-time water management and di. In *IFAC proceedings volumes (IFAC-PapersOnline)*. https://doi.org/10.3182/20080706-5-KR-1001.2220
Chen, Z., & Wang, J. (2010). Land use and land cover change detection using satellite remote sensing techniques in the mountainous Three Gorges Area, China. *International Journal of Remote Sensing, 31*, 1519–1542. https://doi.org/10.1080/01431160903475381
Chew, R., Rineer, J., Beach, R., O'neil, M., Ujeneza, N., Lapidus, D., Miano, T., Hegarty-Craver, M., Polly, J., & Temple, D. S. (2020). Deep neural networks and transfer learning for food crop identification in UAV images. *Drones, 4*, 1–14. https://doi.org/10.3390/drones4010007
Chi, J., & Crawford, M. M. (2014). Spectral unmixing-based crop residue estimation using hyperspectral remote sensing data: A case study at purdue university. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 7*, 2531–2539. https://doi.org/10.1109/JSTARS.2014.2319585
Chughtai, A. H., Abbasi, H., & Karas, I. R. (2021). A review on change detection method and accuracy assessment for land use land cover. *Remote Sensing Applications, 22*, Article 100482. https://doi.org/10.1016/j.rsase.2021.100482
Claassen, R., Bowman, M., Mcfadden, J., Smith, D., & Wallander, S. (2018). *Tillage intensity and conservation cropping in the United States*.
Conrad, C., Lamers, J. P. A., Ibragimov, N., Löw, F., & Martius, C. (2016). Analysing irrigated crop rotation patterns in arid Uzbekistan by the means of remote sensing: A case study on post-soviet agricultural land use. *Journal of Arid Environments, 124*, 150–159. https://doi.org/10.1016/j.jaridenv.2015.08.008
Cracknell, A. P. (2018). The development of remote sensing in the last 40 years. *International Journal of Remote Sensing, 39*, 8387–8427. https://doi.org/10.1080/01431161.2018.1550919
Crowley, M. A., & Cardille, J. A. (2020). Remote sensing's recent and future contributions to landscape ecology. *Current Landscape Ecology Reports, 5*, 45–57. https://doi.org/10.1007/s40823-020-00054-9
Cruz-Ramírez, M., Hervás-Martínez, C., Jurado-Expósito, M., & López-Granados, F. (2012). A multi-objective neural network based method for cover crop identification from remote sensed data. *Expert Systems with Applications, 39*, 10038–10048. https://doi.org/10.1016/j.eswa.2012.02.046
Daughtry, C. S. T., & Hunt, E. R. (2008). Mitigating the effects of soil and residue water contents on remotely sensed estimates of crop residue cover. *Remote Sensing of Environment, 112*, 1647–1657. https://doi.org/10.1016/j.rse.2007.08.006
Daughtry, C. S. T., Hunt, E. R., & Doraiswamy, M. M. (2005). Remote sensing the spatial distribution of crop residues. *Agronomy Journal, 97*, 864–871. https://doi.org/10.2134/agronj2003.0291
Daughtry, C. S. T., Hunt, E. R., Doraiswamy, & Russ, M. M. (2003). Remote sensing of crop residue cover and soil tillage intensity. In *Igarss 2003. 2003 IEEE international geoscience and remote sensing symposium*. IEEE.
Daughtry, C. S. T., McMurtrey, J. E., Chappelle, E. W., Hunter, W. J., & Steiner, J. L. (1996). Measuring crop residue cover using remote sensing techniques. *Theoretical and Applied Climatology, 54*, 17–26.
Davis, A. S., Hill, J. D., Chase, C. A., Johanns, A. M., & Liebman, M. (2012). Increasing cropping system diversity balances productivity, profitability and environmental health. *PLoS One, 7*. https://doi.org/10.1371/journal.pone.0047149
Delavarpour, N., Koparan, C., Nowatzki, J., Bajwa, S., & Sun, X. (2021). A technical study on UAV characteristics for precision agriculture applications and associated practical challenges. *Remote Sensing*. https://doi.org/10.3390/rs13061204
Dian Bah, M., Hafiane, A., & Canals, R. (2018). Deep learning with unsupervised data labeling for weed detection in line crops in UAV images. *Remote Sensing, 10*. https://doi.org/10.3390/rs10111690
Ding, H., Na, J., Jiang, S., Zhu, J., Liu, K., Fu, Y., & Li, F. (2021). Evaluation of three different machine learning methods for object-based artificial terrace mapping—a case study of the loess plateau, China. *Remote Sensing, 13*, 1–19. https://doi.org/10.3390/rs13051021
Dvorakova, K., Shi, P., Limbourg, Q., & van Wesemael, B. (2020). Soil organic carbon mapping from remote sensing: The effect of crop residues. *Remote Sensing, 12*. https://doi.org/10.3390/rs12121913
Estrella, E., Stoeth, A., Krakauer, N. Y., & Devineni, N. (2021). Quantifying vegetation response to environmental changes on the galapagos islands, Ecuador using the normalized difference vegetation index (NDVI). *Environ Res Commun, 3*, Article 065003. https://doi.org/10.1088/2515-7620/ac0bd1
Feng, A., Zhou, J., Vories, E. D., Sudduth, K. A., & Zhang, M. (2020). Yield estimation in cotton using UAV-based multi-sensor imagery. *Biosystems Engineering, 193*, 101–114. https://doi.org/10.1016/j.biosystemseng.2020.02.014
Fisher, J. R. B., Acosta, E. A., Dennedy-Frank, P. J., Kroeger, T., & Boucher, T. M. (2018). Impact of satellite imagery spatial resolution on land use classification accuracy and modeled water quality. *Remote Sens Ecol Conserv, 4*, 137–149. https://doi.org/10.1002/rse2.61
Fonji, S. F., & Taff, G. N. (2014). Using satellite data to monitor land-use land-cover change in North-eastern Latvia. *SpringerPlus, 3*, 1–15.
Franklin, S. E. (2001). *Remote sensing for sustainable forest management*. Taylor and Francis. https://doi.org/10.1201/9781420032857
Galloza, M. S., Crawford, M. M., & Heathman, G. C. (2013). Crop residue modeling and mapping using landsat, ALI, hyperion and airborne remote sensing data. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 6*, 446–456. https://doi.org/10.1109/JSTARS.2012.2222355
Gamba, P., & Houshmand, B. (2010). An efficient neural classification chain of SAR and optical urban images. *International Journal of Remote Sensing, 22*, 1535–1553. https://doi.org/10.1080/01431160118746
Gao, F., Anderson, M. C., & Hively, W. D. (2020). Detecting cover crop end-of-season using venμs and sentinel-2 satellite imagery. *Remote Sensing, 12*, 1–22. https://doi.org/10.3390/rs12213524
García-Berná, J. A., Ouhbi, S., Benmouna, B., García-Mateos, G., Fernández-Alemán, J. L., & Molina-Martínez, J. M. (2020). *Systematic mapping study on remote sensing in agriculture. Applied Sciences (Switzerland)*. https://doi.org/10.3390/app10103456
Gelder, B. K., Kaleita, A. L., & Cruse, R. M. (2009). Estimating mean field residue cover on midwestern soils using satellite imagery. *Agronomy Journal, 101*, 635–643. https://doi.org/10.2134/agronj2007.0249
Ge, Y., Thomasson, J. A., & Sui, R. (2011). Remote sensing of soil properties in precision agriculture: A review. *Frontiers of Earth Science*. https://doi.org/10.1007/s11707-011-0175-0
Ge, X., Wang, J., Ding, J., Cao, X., Zhang, Z., Liu, J., & Li, X. (2019). Combining UAV-based hyperspectral imagery and machine learning algorithms for soil moisture content monitoring. *PeerJ, 7*, Article e6926. https://doi.org/10.7717/peerj.6926
Giovannucci, D., Scherr, S., Nierenberg, D., Hebebrand, C., Shapiro, J., Milder, J., & Wheeler, K. (2012). *Food and agriculture: The future of sustainability. A strategic input to the sustainable development in the 21st century (SD21) project. New york*.
Govender, M., Chetty, K., Naiken, V., & Bulcock, H. (2008). A comparison of satellite hyperspectral and multispectral remote sensing imagery for improved classification and mapping of vegetation. *WaterSA, 34*, 147–154.
Gowda, P. H., Howell, T. A., Evett, S. R., Chavez, J. L., & New, L. (2008). Remote sensing of contrasting tillage practices in the Texas Panhandle. *International Journal of Remote Sensing, 29*, 3477–3487. https://doi.org/10.1080/01431160701581810
Guo, Q., Kelly, M., Gong, P., & Liu, D. (2007). An object-based classification approach in mapping tree mortality using high spatial resolution imagery. *GIsci Remote Sens, 44*, 24–47. https://doi.org/10.2747/1548-1603.44.1.24
Hagen, S. C., Delgado, G., Ingraham, P., Cooke, I., Emery, R., Fisk, J. P., Melendy, L., Olson, T., Patti, S., Rubin, N., Ziniti, B., Chen, H., Salas, W., Elias, P., & Gustafson, D. (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*, 1–23. https://doi.org/10.3390/land9110408
Hartwig, N. L., & Ammon, H. U. (2002). Cover crops and living mulches. *Weed Science, 50*, 688–699. https://doi.org/10.1614/0043-1745(2002)050[0688:aiacca]2.0.co;2
Hasituya, Chen, Z., Li, F., & Hongmei. (2017). Mapping Plastic-Mulched Farmland with C-band full polarization SAR remote sensing data. *Remote Sensing, 9*. https://doi.org/10.3390/rs9121264
Hasituya, Chen, Z., Wang, L., & Liu, J. (2017b). Selecting appropriate spatial scale for mapping plastic-mulched farmland with satellite remote sensing imagery. *Remote Sensing, 9*. https://doi.org/10.3390/rs9030265
Hasituya, Zhongxin, C., Fei, L., & Yuncai, H. (2020). Mapping plastic-mulched farmland by coupling optical and synthetic aperture radar remote sensing. *International Journal of Remote Sensing, 41*, 7757–7778. https://doi.org/10.1080/01431161.2020.1763510
Hassan-Esfahani, L., Torres-Rua, A., Jensen, A., & McKee, M. (2015). Assessment of surface soil moisture using high-resolution multi-spectral imagery and artificial neural networks. *Remote Sensing, 7*, 2627–2646. https://doi.org/10.3390/rs70302627
Hively, W. D., Duiker, S., McCarty, G., & Prabhakara, K. (2015). Remote sensing to monitor cover crop adoption in southeastern Pennsylvania. *Journal of Soil and Water Conservation, 70*, 340–352. https://doi.org/10.2489/jswc.70.6.340
Hively, W. D., Lamb, B. T., Daughtry, C. S. T., Shermeyer, J., McCarty, G. W., & Quemada, M. (2018). Mapping crop residue and tillage intensity using WorldView-3 satellite shortwave infrared residue indices. *Remote Sensing, 10*. https://doi.org/10.3390/rs10101657

Hively, W. D., Lang, M., McCarty, G. W., Keppler, J., Sadeghi, A., & McConnell, L. L. (2009). Using satellite remote sensing to estimate winter cover crop nutrient uptake efficiency. *Journal of Soil and Water Conservation, 64*, 303–313. https://doi.org/10.2489/jswc.64.5.303

Hively, W. D., Lee, S., Sadeghi, A. M., McCarty, G. W., Lamb, B. T., Soroka, A., Keppler, J., Yeo, I. Y., & Moglen, G. E. (2020). Estimating the effect of winter cover crops on nitrogen leaching using cost-share enrollment data, satellite remote sensing, and Soil and Water Assessment Tool (SWAT) modeling. *Journal of Soil and Water Conservation, 75*, 362–375. https://doi.org/10.2489/JSWC.75.3.362

Hively, W. D., Shermeyer, J., Lamb, B. T., Daughtry, C. T., Quemada, M., & Keppler, J. (2019). Mapping crop residue by combining landsat and worldview-3 satellite imagery. *Remote Sensing, 11*. https://doi.org/10.3390/rs11161857

Hobbs, P. R., Sayre, K., & Gupta, R. (2008). *The role of conservation agriculture in sustainable agriculture*. Philosophical Transactions of the Royal Society B: Biological Sciences. https://doi.org/10.1098/rstb.2007.2169

Huang, H., & Roy, D. P. (2021). Characterization of Planetscope-0 Planetscope-1 surface reflectance and normalized difference vegetation index continuity. *Science of Remote Sensing, 3*, Article 100014. https://doi.org/10.1016/j.srs.2021.100014

Huggins, D. R., & Reganold, J. P. (2008). *No-till: The quiet revolution*.

Hung, C., Xu, Z., & Sukkarieh, S. (2014). Feature learning based approach for weed classification using high resolution aerial images from a digital camera mounted on a UAV. *Remote Sensing, 6*, 12037–12054. https://doi.org/10.3390/rs61212037

Hunt, R., & Daughtry, C. (2018). What good are unmanned aircraft systems for agricultural remote sensing and precision agriculture? *International Journal of Remote Sensing, 39*, 5345–5376. https://doi.org/10.1080/01431161.2017.1410300

Hunt, E. R., Hively, W., McCarty, G., Daughtry, C., Forrestal, P., Kratochvil, R., Carr, J., Allen, N., Fox-Rabinovitz, J., & Miller, C. (2011). NIR-green-blue high-resolution digital images for assessment of winter cover crop biomass. *GIsci Remote Sens, 48*, 86–98. https://doi.org/10.2747/1548-1603.48.1.86

Jayanth, J., Aravind, R., & Amulya, C. M. (2021). Classification of crops and crop rotation using remote sensing and GIS-based approach: A case study of doddakawalande hobli, nanjangudu taluk. *Journal of the Indian Society of Remote Sensing*. https://doi.org/10.1007/s12524-020-01296-0

Kasischke, E. S., Melack, J. M., & Dobson, M. C. (1997). The use of imaging radars for ecological applications - a review. *Remote Sensing of Environment, 59*, 141–156. https://doi.org/10.1016/S0034-4257(96)00148-4

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*. https://doi.org/10.3390/rs13142689

Khanal, S., Fulton, J., & Shearer, S. (2017). An overview of current and potential applications of thermal remote sensing in precision agriculture. *Computers and Electronics in Agriculture*. https://doi.org/10.1016/j.compag.2017.05.001

Koger, C. H., Shaw, D. R., Reddy, K. N., & Bruce, L. M. (2004). Detection of pitted morningglory (Ipomoea lacunosa) by hyperspectral remote sensing. 1. Effects of tillage and cover crop residue. *Source: Weed Science, 52*, 222–229.

Koutsos, T. M., Menexes, G. C., & Dordas, C. A. (2019). *An efficient framework for conducting systematic literature reviews in agricultural sciences*. Science of the Total Environment. https://doi.org/10.1016/j.scitotenv.2019.04.354

Laamrani, A., Joosse, P., McNairn, H., Berg, A. A., Hagerman, J., Powell, K., & Berry, M. (2020). Assessing soil cover levels during the non-growing season using multitemporal satellite imagery and spectral unmixing techniques. *Remote Sensing, 12*. https://doi.org/10.3390/RS12091397

Lan, Y., Huang, K., Yang, C., Lei, L., Ye, J., Zhang, J., Zeng, W., Zhang, Y., & Deng, J. (2021). Real-time identification of rice weeds by uav low-altitude remote sensing based on improved semantic segmentation model. *Remote Sensing, 13*. https://doi.org/10.3390/rs13214370

Lausch, A., Baade, J., Bannehr, L., Borg, E., Bumberger, J., Chabrilliat, S., Dietrich, P., Gerighausen, H., Glässer, C., Hacker, J. M., Haase, D., Jagdhuber, T., Jany, S., Jung, A., Karnieli, A., Kraemer, R., Makki, M., Mielke, C., Möller, M., … Schaepman, M. E. (2019). Linking remote sensing and geodiversity and their traits relevant to biodiversity-Part I: Soil characteristics. *Remote Sensing*. https://doi.org/10.3390/rs11202356

Leek, R., & Solberg, R. (1995). Using remote sensing for monitoring of autumn tillage in Norway. *International Journal of Remote Sensing, 16*, 447–466. https://doi.org/10.1080/01431169508954412

Lehman, R. M., Cambardella, C. A., Stott, D. E., Acosta-Martinez, V., Manter, D. K., Buyer, J. S., Maul, J. E., Smith, J. L., Collins, H. P., Halvorson, J. J., Kremer, R. J., Lundgren, J. G., Ducey, T. F., Jin, V. L., & Karlen, D. L. (2015). Understanding and enhancing soil biological health: The solution for reversing soil degradation. *Sustainability, 7*, 988–1027. https://doi.org/10.3390/su7010988

Liberati, A., Altman, D. G., Tetzlaff, J., Mulrow, C., Gøtzsche, P. C., Ioannidis, J. P. A., Clarke, M., Devereaux, P. J., Kleijnen, J., & Moher, D. (2009). The PRISMA statement for reporting systematic reviews and meta-analyses of studies that evaluate health care interventions: Explanation and elaboration. *Journal of Clinical Epidemiology*, e1–e34. https://doi.org/10.1016/j.jclinepi.2009.06.006

Liu, D., & Xia, F. (2010). Assessing object-based classification: Advantages and limitations. *Remote Sensing Letters*. https://doi.org/10.1080/01431161003743173

Liu, C., Zhang, Q., Tao, S., Qi, J., Ding, M., Guan, Q., Wu, B., Zhang, M., Nabil, M., Tian, F., Zeng, H., Zhang, N., Bavuudorj, G., Rukundo, E., Liu, W., Bofana, J., Beyene, A. N., & Elnashar, A. (2020). A new framework to map fine resolution cropping intensity across the globe: Algorithm, validation, and implication. *Remote Sensing of Environment, 251*. https://doi.org/10.1016/j.rse.2020.112095

Liu, J., Zhu, W., Atzberger, C., Zhao, A., Pan, Y., & Huang, X. (2018). A phenology-based method to map cropping patterns under a wheat-maize rotation using remotely sensed time-series data. *Remote Sensing, 10*. https://doi.org/10.3390/rs10081203

Li, R., Xu, M., Chen, Z., Gao, B., Cai, J., Shen, F., He, X., Zhuang, Y., & Chen, D. (2021). Phenology-based classification of crop species and rotation types using fused MODIS and Landsat data: The comparison of a random-forest-based model and a decision-rule-based model. *Soil and Tillage Research, 206*. https://doi.org/10.1016/j.still.2020.104838

Lizotte, R. E., Smiley, P. C., Gillespie, R. B., & Knight, S. S. (2021). *Agricultural conservation practices and aquatic ecological responses, 13*. Switzerland: Water. https://doi.org/10.3390/w13121687

Luo, W., Xu, X., Liu, W., Liu, M., Li, Z., Peng, T., Xu, C., Zhang, Y., & Zhang, R. (2019). UAV based soil moisture remote sensing in a karst mountainous catchment. *Catena, 174*, 478–489. https://doi.org/10.1016/j.catena.2018.11.017

Lu, D., & Weng, Q. (2007). A survey of image classification methods and techniques for improving classification performance. *International Journal of Remote Sensing*. https://doi.org/10.1080/01431160600746456

Maas, S. J., & Rajan, N. (2008). Estimating ground cover of field crops using medium-resolution multispectral satellite imagery. *Agronomy Journal, 100*, 320–327. https://doi.org/10.2134/agronj2007.0140

Maes, W. H., & Steppe, K. (2019). Perspectives for remote sensing with unmanned aerial vehicles in precision agriculture. *Trends in Plant Science*. https://doi.org/10.1016/j.tplants.2018.11.007

Magdoff, F., & van Es, H. (2009). *Building soils for better crops: Ecological management for healthy soils*.

Mahdianpari, M., Granger, J. E., Mohammadimanesh, F., Salehi, B., Brisco, B., Homayouni, S., Gill, E., Huberty, B., & Lang, M. (2020). Meta-analysis of wetland classification using remote sensing: A systematic review of a 40-year trend in north America. *Remote Sensing, 12*, 1882. https://doi.org/10.3390/RS12111882

Manjunath, K. R., More, R. S., Jain, N. K., Panigrahy, S., & Parihar, J. S. (2015). Mapping of rice-cropping pattern and cultural type using remote-sensing and ancillary data: A case study for South and southeast asian countries. *International Journal of Remote Sensing, 36*, 6008–6030. https://doi.org/10.1080/01431161.2015.1110259

Martins, V. S., Kaleita, A. L., & Gelder, B. K. (2021). Digital mapping of structural conservation practices in the Midwest U.S. croplands: Implementation and preliminary analysis. *Science of the Total Environment, 772*. https://doi.org/10.1016/j.scitotenv.2021.145191

Moher, D., Liberati, A., Tetzlaff, J., & Altman, D. G. (2009). Preferred reporting items for systematic reviews and meta-analyses: The PRISMA statement. *Journal of Clinical Epidemiology, 62*, 1006–1012. https://doi.org/10.1016/j.jclinepi.2009.06.005

Möller, M., Lymburner, L., & Volk, M. (2007). The comparison index: A tool for assessing the accuracy of image segmentation. *International Journal of Applied Earth Observation and Geoinformation, 9*, 311–321. https://doi.org/10.1016/J.JAG.2006.10.002

Muñoz, J. D., Finley, A. O., Gehl, R., & Kravchenko Sasha, S. (2010). Nonlinear hierarchical models for predicting cover crop biomass using Normalized Difference Vegetation Index. *Remote Sensing of Environment, 114*, 2833–2840. https://doi.org/10.1016/j.rse.2010.06.011

Najafi, P., Feizizadeh, B., & Navid, H. (2021). A comparative approach of fuzzy object based image analysis and machine learning techniques which are applied to crop residue cover mapping by using sentinel-2 satellite and uav imagery. *Remote Sensing, 13*, 1–24. https://doi.org/10.3390/rs13050937

Najafi, P., Navid, H., Feizizadeh, B., & Eskandari, I. (2018). Object-based satellite image analysis applied for crop residue estimating using Landsat OLI imagery. *International Journal of Remote Sensing, 39*, 6117–6136. https://doi.org/10.1080/01431161.2018.1454621

Navarro, E., Costa, N., & Pereira, A. (2020). A systematic review of iot solutions for smart farming. *Sensors*. https://doi.org/10.3390/s20154231

Nevavuori, P., Narra, N., Linna, P., & Lipping, T. (2020). Crop yield prediction using multitemporal UAV data and spatio-temporal deep learning models. *Remote Sensing, 12*, 1–18. https://doi.org/10.3390/rs12234000

Nevavuori, P., Narra, N., & Lipping, T. (2019). Crop yield prediction with deep convolutional neural networks. *Computers and Electronics in Agriculture, 163*. https://doi.org/10.1016/j.compag.2019.104859

Nowak, B., Marliac, G., & Michaud, A. (2021). Estimation of winter soil cover by vegetation before spring-sown crops for mainland France using multispectral satellite imagery. *Environmental Research Letters, 16*. https://doi.org/10.1088/1748-9326/ac007c

Obade, V. de P., & Gaya, C. (2020). Mapping tillage practices using spatial information techniques. *Environmental Management, 66*, 722–731. https://doi.org/10.1007/s00267-020-01335-z

Pacheco, A., Bannari, A., Staenz, K., & McNairn, H. (2008). Deriving percent crop cover over agriculture canopies using hyperspectral remote sensing. *Canadian Journal of Remote Sensing*.

Pacheco, A., & McNairn, H. (2010). Evaluating multispectral remote sensing and spectral unmixing analysis for crop residue mapping. *Remote Sensing of Environment, 114*, 2219–2228. https://doi.org/10.1016/j.rse.2010.04.024

Page, K. L., Dang, Y. P., & Dalal, R. C. (2020). The ability of conservation agriculture to conserve soil organic carbon and the subsequent impact on soil physical, chemical, and biological properties and yield. *Frontiers in Sustainable Food Systems*. https://doi.org/10.3389/fsufs.2020.00031

Page, M. J., McKenzie, J. E., Bossuyt, P. M., Boutron, I., Hoffmann, T. C., Mulrow, C. D., Shamseer, L., Tetzlaff, J. M., Akl, E. A., Brennan, S. E., Chou, R., Glanville, J., Grimshaw, J. M., Hróbjartsson, A., Lalu, M. M., Li, T., Loder, E. W., Mayo-Wilson, E., McDonald, S., … Moher, D. (2021). The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ, 372*. https://doi.org/10.1136/BMJ.N71

Panigrahy, S., & Sharma, S. A. (1997). Mapping of crop rotation using multidate Indian Remote Sensing Satellite digital data. *ISPRS Journal of Photogrammetry and Remote Sensing*.

Pearlman, J., Carman, S., Segal, C., Jarecke, P., Clancy, P., & Browne, W. (2001). Overview of the Hyperion imaging spectrometer for the NASA EO-1 mission. *International Geoscience and Remote Sensing Symposium (IGARSS), 7*, 3036–3038. https://doi.org/10.1109/IGARSS.2001.978246

Pittelkow, C. M., Liang, X., Linquist, B. A., Van Groenigen, L. J., Lee, J., Lundy, M. E., Van Gestel, N., Six, J., Venterea, R. T., & Van Kessel, C. (2015). Productivity limits and potentials of the principles of conservation agriculture. *Nature, 517*, 365–368. https://doi.org/10.1038/nature13809

Prabhakara, K., Dean Hively, W., & McCarty, G. W. (2015). Evaluating the relationship between biomass, percent groundcover and remote sensing indices across six winter cover crop fields in Maryland, United States. *International Journal of Applied Earth Observation and Geoinformation, 39*, 88–102. https://doi.org/10.1016/j.jag.2015.03.002

Prokopy, L. S., Floress, K., Arbuckle, J. G., Church, S. P., Eanes, F. R., Gao, Y., Gramig, B. M., Ranjan, P., & Singh, A. S. (2019). Adoption of agricultural conservation practices in the United States: Evidence from 35 years of quantitative literature. *Journal of Soil and Water Conservation, 74*, 520–534. https://doi.org/10.2489/jswc.74.5.520

Radočaj, D., Obhođaš, J., Jurišić, M., & Gašparović, M. (2020). *Global open data remote sensing satellite missions for land monitoring and conservation: A review. Land (basel)*. https://doi.org/10.3390/land9110402

Rogan, J., & Chen, D. M. (2004). Remote sensing technology for mapping and monitoring land-cover and land-use change. *Progress in Planning, 61*, 301–325. https://doi.org/10.1016/S0305-9006(03)00066-7

Schreier, J., Ghazaryan, G., & Dubovyk, O. (2021). Crop-specific phenomapping by fusing Landsat and Sentinel data with MODIS time series. *Eur J Remote Sens, 54*, 47–58. https://doi.org/10.1080/22797254.2020.1831969

Seifert, C. A., Azzari, G., & Lobell, D. B. (2019). Corrigendum: Satellite detection of cover crops and their effects on crop yield in the Midwestern United States. *Environmental Research Letters, 14*. https://doi.org/10.1088/1748-9326/aaf933

Serbin, G., Daughtry, C., Hunt, E., Brown, D., & McCarty, G. (2009a). Effect of soil spectral properties on remote sensing of crop residue cover. *Soil & Water Management & Conservation, 73*, 1545–1558. https://doi.org/10.2136/sssaj2008.0311

Serbin, G., Daughtry, C., Hunt, E., Reeves, J., & Brown, D. (2009b). Effects of soil composition and mineralogy on remote sensing of crop residue cover. *Remote Sensing of Environment, 113*, 224–238. https://doi.org/10.1016/j.rse.2008.09.004

Serbin, G., Hunt, E., Daughtry, C., McCarty, G., & Doraiswamy, P. (2009c). An improved ASTER index for remote sensing of crop residue. *Remote Sensing, 1*, 971–991. https://doi.org/10.3390/rs1040971

Sharpley, A., Daniels, M., Berry, L., Hallmark, C., & Hesselbein, J. (2015). Arkansas discovery farms: Documenting water quality benefits of on-farm conservation management and empowering farmers. *Acta Agric Scand B Soil Plant Sci, 65*, 186–198. https://doi.org/10.1080/09064710.2014.960444

Shi, X., Han, W., Zhao, T., & Tang, J. (2019). Decision support system for variable rate irrigation based on UAV multispectral remote sensing. *Sensors, 19*. https://doi.org/10.3390/s19132880

Smith, A. M., Major, D. J., Lindwall, C. W., & Brown, R. J. (1995). Multi-temporal, multi-sensor remote sensing for monitoring soil conservation farming. *Canadian Journal of Remote Sensing, 21*, 177–184. https://doi.org/10.1080/07038992.1995.10874611

Song, M., Civco, D. L., & Hurd, J. D. (2011). A competitive pixel-object approach for land cover classification. *International Journal of Remote Sensing, 26*, 4981–4997. https://doi.org/10.1080/01431160500213912

Sonmez, N. K., & Slater, B. (2016). Measuring intensity of tillage and plant residue cover using remote sensing. *Eur J Remote Sens, 49*, 121–135. https://doi.org/10.5721/EuJRS20164907

Sood, A., Choudhury, B., Ray, S., Jalota, S., Sharma, P., Panigrahy, S., Choudhury, S., Ray, S. S., Jalota, S. K., Sharma, P. K., & Shushma Panigrahy, A. B. (2009). Impact of cropping pattern changes on the exploitation of water resources: A remote sensing and gis approach. *J. Indian Soc. Remote Sens.*

South, S., Qi, J., & Lusch, D. P. (2004). Optimal classification methods for mapping agricultural tillage practices. *Remote Sensing of Environment, 91*, 90–97. https://doi.org/10.1016/j.rse.2004.03.001

Stroppiana, D., Migliazzi, M., Chiarabini, V., Crema, A., Musanti, M., Franchino, C., & Villa, P. (2015). Rice yield estimation using multispectral data from UAV: A preliminary experiment in northern Italy. In *2015 IEEE international geoscience and remote sensing symposium (IGARSS)* (pp. 4664–4667).

Sudheer, K. P., Gowda, P., Chaubey, I., & Howell, T. (2010). Artificial Neural Network approach for mapping contrasting tillage practices. *Remote Sensing, 2*, 579–590. https://doi.org/10.3390/rs2020579

Tao, H., Feng, H., Xu, L., Miao, M., Long, H., Yue, J., Li, Z., Yang, G., Yang, X., & Fan, L. (2020). Estimation of crop growth parameters using UAV- based hyperspectral remote sensing data. *Sensors, 20*. https://doi.org/10.3390/s20051296

Teasdale, J. R. (1996). Contribution of cover crops to weed management in sustainable agricultural systems. *Journal of Production Agriculture, 9*, 475–479.

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 of the United States of America, 118*, 1–8. https://doi.org/10.1073/pnas.1922375118

Thieme, A., Yadav, S., Oddo, P. C., Fitz, J. M., McCartney, S., King, L. A., Keppler, J., McCarty, G. W., & Hively, W. D. (2020). Using NASA Earth observations and Google Earth Engine to map winter cover crop conservation performance in the Chesapeake Bay watershed. *Remote Sensing of Environment, 248*. https://doi.org/10.1016/j.rse.2020.111943

Uri, N. D. (2001). The environmental implications of soil erosion in the United States. *Environmental Monitoring and Assessment, 66*, 293–312.

Ustuner, M., Sanli, F. B., Abdikan, S., Esetlili, M. T., & Kurucu, Y. (2014). Crop type classification using vegetation indices of rapideye imagery. In *International archives of the photogrammetry, remote sensing and spatial information sciences - ISPRS archives* (pp. 195–198). International Society for Photogrammetry and Remote Sensing. https://doi.org/10.5194/isprsarchives-XL-7-195-2014.

Van Deventer, A. P., Ward, A. D., Gowda, P. H., & Lyon, J. G. (1997). Using thematic mapper data to identify contrasting soil plains and tillage practices. *Photogrammetric Engineering & Remote Sensing, 63*, 87–93.

Viña, A., Peters, A. J., & Ji, L. (2003). *Use of multispectral ikonos imagery for discriminating between conventional and conservation agricultural tillage practices*. Photogrammetric Engineering & Remote Sensing.

Waldhoff, G., Lussem, U., & Bareth, G. (2017). Multi-data approach for remote sensing-based regional crop rotation mapping: A case study for the rur catchment, Germany. *International Journal of Applied Earth Observation and Geoinformation, 61*, 55–69. https://doi.org/10.1016/j.jag.2017.04.009

Wallace, J. F., Caccetta, P. A., & Kiiveri, H. T. (2004). Recent developments in analysis of spatial and temporal data for landscape qualities and monitoring. *Austral Ecology, 29*, 100–107. https://doi.org/10.1111/J.1442-9993.2004.01356.X

Watts, J. D., Powell, S. L., Lawrence, R. L., & Hilker, T. (2011). Improved classification of conservation tillage adoption using high temporal and synthetic satellite imagery. *Remote Sensing of Environment, 115*, 66–75. https://doi.org/10.1016/j.rse.2010.08.005

Weiss, M., Jacob, F., & Duveiller, G. (2020). Remote sensing for agricultural applications: A meta-review. *Remote Sensing of Environment, 236*. https://doi.org/10.1016/j.rse.2019.111402

Wulder, M. A., Franklin, S. E., Hall, R. J., & Coops, N. C. (2004). High spatial resolution remotely sensed data for ecosystem characterization. *BioScience*.

Wulder, M. A., Loveland, T. R., Roy, D. P., Crawford, C. J., Masek, J. G., Woodcock, C. E., Allen, R. G., Anderson, M. C., Belward, A. S., Cohen, W. B., Dwyer, J., Erb, A., Gao, F., Griffiths, P., Helder, D., Hermosilla, T., Hipple, J. D., Hostert, P., Hughes, M. J., … Zhu, Z. (2019). Current status of Landsat program, science, and applications. *Remote Sensing of Environment, 225*, 127–147. https://doi.org/10.1016/j.rse.2019.02.015

Xiong, Y., Zhang, Q., Chen, X., Bao, A., Zhang, J., & Wang, Y. (2019). Large scale agricultural plastic mulch detecting and monitoring with multi-source remote sensing data: A case study in Xinjiang, China. *Remote Sensing, 11*. https://doi.org/10.3390/rs11182088

Xu, M., Lacey, C. G., & Armstrong, S. D. (2018). The feasibility of satellite remote sensing and spatial interpolation to estimate cover crop biomass and nitrogen uptake in a small watershed. *Journal of Soil and Water Conservation, 73*, 682–692. https://doi.org/10.2489/jswc.73.6.682

Xun, L., Zhang, J., Cao, D., Wang, J., Zhang, S., & Yao, F. (2021). Mapping cotton cultivated area combining remote sensing with a fused representation-based classification algorithm. *Computers and Electronics in Agriculture, 181*. https://doi.org/10.1016/j.compag.2020.105940

Yang, S., Hu, L., Wu, H., Ren, H., Qiao, H., Li, P., & Fan, W. (2021). Integration of crop growth model and random forest for winter wheat yield estimation from UAV hyperspectral imagery. *Ieee Journal of Selected Topics in Applied Earth Observations and Remote Sensing, 14*, 6253–6269. https://doi.org/10.1109/JSTARS.2021.3089203

Yang, G., Liu, J., Zhao, C., Li, Z., Huang, Y., Yu, H., Xu, B., Yang, X., Zhu, D., Zhang, X., Zhang, R., Feng, H., Zhao, X., Li, Z., Li, H., & Yang, H. (2017). Unmanned aerial vehicle remote sensing for field-based crop phenotyping: Current status and perspectives. *Frontiers of Plant Science*. https://doi.org/10.3389/fpls.2017.01111

Yang, Q., Shi, L., Han, J., Yu, J., & Huang, K. (2020). A near real-time deep learning approach for detecting rice phenology based on UAV images. *Agricultural and Forest Meteorology, 287*. https://doi.org/10.1016/j.agrformet.2020.107938

Yan, S., Yao, X., Zhu, D., Liu, D., Zhang, L., Yu, G., Gao, B., Yang, J., & Yun, W. (2021). Large-scale crop mapping from multi-source optical satellite imageries using machine learning with discrete grids. *International Journal of Applied Earth Observation and Geoinformation, 103*. https://doi.org/10.1016/j.jag.2021.102485

Yue, J., & Tian, Q. (2020). Estimating fractional cover of crop, crop residue, and soil in cropland using broadband remote sensing data and machine learning. *International Journal of Applied Earth Observation and Geoinformation, 89*, Article 102089. https://doi.org/10.1016/j.jag.2020.102089

Zhang, J., Wang, C., Yang, C., Xie, T., Jiang, Z., Hu, T., Luo, Z., Zhou, G., & Xie, J. (2020). Assessing the effect of real spatial resolution of in situ UAV multispectral images on seedling rapeseed growth monitoring. *Remote Sensing, 12*, 1–18. https://doi.org/10.3390/rs12081207

Zhao, D., Yang, T., & An, S. (2012). Effects of crop residue cover resulting from tillage practices on LAI estimation of wheat canopies using remote sensing. *International Journal of Applied Earth Observation and Geoinformation, 14*, 169–177. https://doi.org/10.1016/j.jag.2011.09.003

Zhao, F., Yang, G., Yang, X., Cen, H., Zhu, Y., Han, S., Yang, H., He, Y., & Zhao, C. (2021). Determination of key phenological phases ofwinter wheat based on the time-weighted dynamic time warping algorithm and MODIS time-series data. *Remote Sensing, 13*. https://doi.org/10.3390/rs13091836

Zheng, B., Campbell, J., & de Beurs, K. (2012). Remote sensing of crop residue cover using multi-temporal Landsat imagery. *Remote Sensing of Environment, 117*, 177–183. https://doi.org/10.1016/j.rse.2011.09.016

Zheng, B., Campbell, J., Serbin, G., & Daughtry, C. (2013). Multitemporal remote sensing of crop residue cover and tillage practices: A validation of the minNDTI strategy in the United States. *Journal of Soil and Water Conservation, 68*, 120–131. https://doi.org/10.2489/jswc.68.2.120

Zheng, B., Campbell, J., Serbin, G., & Galbraith, J. (2014). Remote sensing of crop residue and tillage practices: Present capabilities and future prospects. *Soil and Tillage Research, 138*, 26–34. https://doi.org/10.1016/J.STILL.2013.12.009

Zheng, B., Campbell, J., Shao, Y., & Wynne, R. (2013). Broad-scale monitoring of tillage practices using sequential landsat imagery. *Soil Science Society of America Journal, 77*, 1755–1764. https://doi.org/10.2136/sssaj2013.03.0108

Zhou, K., Cheng, T., Zhu, Y., Cao, W., Ustin, S., Zheng, H., Yao, X., & Tian, Y. (2018). Assessing the impact of spatial resolution on the estimation of leaf nitrogen concentration over the full season of paddy rice using near-surface imaging spectroscopy data. *Frontiers of Plant Science, 9*. https://doi.org/10.3389/fpls.2018.00964