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Analyzing the Adoption, Cropping Rotation, and Impact of Winter Cover Crops in the Mississippi Alluvial Plain (MAP) Region through Remote Sensing Technologies

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Analyzing the Adoption, Cropping Rotation, and Impact of Winter Cover Crops in the Mississippi Alluvial Plain (MAP) Region through Remote Sensing Technologies

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by

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ABSTRACT

This dissertation explores the application of remote sensing technologies in conservation agriculture, specifically focusing on identifying and mapping winter cover crops and assessing voluntary cover crop adoption and cropping patterns in the Arkansas portion of the Mississippi Alluvial Plain (MAP). In the first chapter, a systematic review using the PRISMA methodology examines the last 30 years of thematic research, development, and trends in remote sensing applied to conservation agriculture from a global perspective. The review uncovers a growing interest in remote sensing-based research in conservation agriculture and emphasizes the necessity for further studies dedicated to conservation practices. Among the 68 articles examined, 94% of studies utilized a pixel-based classification method, while only 6% employed an object-based approach. The analysis also revealed a thematic shift over time, with tillage practices being extensively studied before 2005, followed by a focus on crop residue from 2004 to 2012. From 2012 to 2020, there was a renewed emphasis on cover crops research. These findings highlight the evolving research landscape and provide insights into the trends within remote sensing-based conservation agriculture studies. The second chapter presents a methodological framework for identifying and mapping winter cover crops. The framework utilizes the Google Earth Engine (GEE) and a Random Forest (RF) classifier with time series data from Landsat 8 satellite. Results demonstrate a high classification accuracy (97.7%) and a significant increase (34%) in model-predicted cover crop adoption over the study period between 2013 and 2019. Additionally, the study showcases the use of multi-year datasets to efficiently map the growing season's length and cover crops' phenological characteristics. The third chapter assesses the voluntary adoption of winter cover crops and cropping patterns in the MAP region. Remote sensing technologies, USDA-NRCS government cover crop data sources, and the USDA

Cropland Data Layer (CDL) are employed to identify cover crop locations, analyze county-wide voluntary adoption, and cropping rotations. The result showed a 5.33% increase in the overall voluntary adoption of cover crops in the study region between 2013 and 2019. The findings also indicate a growing trend in cover crop adoption, with soybean-cover crop rotations being prominent. This dissertation enhances our understanding of the role of remote sensing in conservation agriculture with a particular focus on winter cover crops. These insights are valuable for policymakers, stakeholders, and researchers seeking to promote sustainable agricultural practices and increased cover crop adoption. The study also underscores the significance of integrating remote sensing technologies into agricultural decision-making processes and highlights the importance of collaboration among policymakers, researchers, and producers. By leveraging the capabilities of remote sensing, it will enhance conservation agriculture contribution to long-term environmental sustainability and agricultural resilience.
Keywords: Remote sensing technologies, Conservation agriculture, Winter cover crops, Voluntary adoption, Cropping patterns, Sustainable agricultural practices

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DEDICATION

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CHAPTER 3: WINTER COVER CROP IDENTIFICATION: A REMOTE SENSING-BASED METHODOLOGICAL FRAMEWORK FOR NEW AND RAPID DATA GENERATION.

Citation

Ahmed, Z., Nalley, L., Brye, K., Green, V. S., Popp, M., Shew, A., & Connor, L. (2023). Winter Cover Crop Identification: A Remote Sensing-based Methodological Framework for New and Rapid Data Generation. International Journal of Applied Earth Observation and Geoinformation. Manuscript Id: JAG-D-23-01144 (Submitted- in review)

CHAPTER 1: INTRODUCTION

As one of the most essential human activities, agriculture has been at the heart of human survival and progress, shaping societies and powering economies. But as humanity has modernized its agricultural systems, it has often failed to account for the toll these practices can take on its natural resources, specifically the soil. This dissertation seeks to tackle the nexus of agricultural production and sustainability, focusing on adopting sustainable farming practices and technologies in the Arkansas portion of the Mississippi Alluvial Plain (MAP) region.

The first chapter of this dissertation, titled "An examination of thematic research, development, and trends in remote sensing applied to conservation agriculture," analyzes related scholarly work and highlights the application of remote sensing strategies and techniques, solely within the context of conservation agriculture, from a global perspective, from 1991 to 2021. The methodology is built upon a systematic literature analysis, deploying a suite of keywords, Boolean operators, and wildcards to yield pertinent outcomes. The search focuses on article titles rather than abstracts or complete manuscripts, ensuring topic-specific literature and reducing false-positive articles. Transparency is ensured by adopting the PRISMA methodology and protocol framework for systematic literature reviews. This comprehensive study provides valuable insights into the application of remote sensing in conservation agriculture, aiming to identify trends and developments in this field, emphasizing the thematic nature of the research due to the lack of literature on this aspect.

The study aims to fulfill several objectives, including examining the thematic nature of remote sensing applied to conservation agriculture, identifying trends and developments in this field, and providing a comprehensive literature review. It focuses on five agricultural conservation practices: cover crops, crop residue, crop rotation, mulching, and tillage practices, employing a systematic process for assessing and evaluating remote sensing techniques. Guided by the main research question of how remote sensing tools, techniques, algorithms, and methods are applied to conservation agriculture, this study stands out by gathering and examining a diverse array of studies from different regions and countries. It offers a summarization and global perspective on remote sensing tools, techniques, and methods used in the five essential conservation practice categories, which have not been adequately addressed in previous reviews (Ali et al., 2015; Babaeian et al., 2019; García-Berná et al., 2020; Khanal et al., 2017; Lausch et al., 2019; Lizotte et al., 2021; Nasir Ahmad et al., 2020; Navarro et al., 2020; Prokopy et al., 2019; Weiss et al., 2020).

By highlighting gaps in the existing literature and providing recommendations for future research, this evaluation serves as a valuable resource for developing more advanced and efficient remote sensing tools, techniques, and methods tailored for conservation agriculture and its principles. Furthermore, the study offers insights into potential future applications in conservation agriculture research. The novelty of this research lies in its categorical and thematic approach, countering the gap in available literature in this dimension. It also provides a snapshot of various agricultural conservation methods and sheds light on the common remote sensing tools, methods, and algorithms used to identify these practices. The results of this study, representing a relatively comprehensive examination of remote sensing for conservation agriculture, will be helpful to conservation scholars, researchers, and policymakers interested in conservation research on both domestic and international levels.

Building on this, chapter two, titled "Winter Cover Crop Identification: A Remote Sensing-based Methodological Framework for New and Rapid Data Generation," focuses on winter cover crops in the Arkansas portion of Mississippi Alluvial Plain (MAP), a region that has been subjected to intensive farming practices leading to soil erosion and nutrient leaching (Basche et al., 2016; Dabney et al., 2001). In this context, the chapter presents a compelling case for adopting winter cover crops as a key strategy for preserving soil health and productivity during the non-cash cropping season, when fields are often left bare and vulnerable to erosive forces. In the United States, although the adoption of winter cover crops is not a new agricultural practice, its extensive array of environmental and economic advantages has recently garnered the interest of producers and policymakers. Consequently, there was a 50% increase in the reported area dedicated to cover crop planting in the United States between 2012 and 2017 (Wallander et al., 2021).

Despite the significant increase in government incentives funding to encourage cover crop adoption since 2012 (Wallander et al., 2021), there is still a lack of clarity regarding the geographical distribution and total area of these adopted cover crops. This lack of clarity arises from the absence of ground-truthed spatial data and a reliable method for accurately identifying the locations where cover crops are being adopted.

With the advancement of novel remote sensing tools and techniques, researchers can swiftly conduct research projects with improved data accuracy, often at a minimal cost and with reduced labor requirements. The agricultural sector has widely embraced the use of remotely sensed data due to its inherent user-friendliness. Previous research studies have employed multiple satellite imagery datasets, as well as spectral and vegetation indices, to effectively identify, understand, categorize, monitor, and evaluate winter cover crops across various geographic scales (Hagen et al., 2020; Hively et al., 2015; Kc et al., 2021; Rundquist & Carlson, 2017; Seifert et al., 2018; Thieme et al., 2020). However, when it comes to cover crop identification and monitoring, remote sensing techniques have been primarily limited to smaller areas, typically ranging from a few acres to a few hundred acres. Studies focusing on larger areas, accompanied by ground truthing, are scarce or rely on less accurate methods, such as windshield surveys, which are prone to errors and possess low GPS precision, revealing a significant research gap. Besides, no single research has been conducted for identifying cover crops and their adoption in heterogeneous landscapes and one of the key agricultural regions in the United States, the MAP region.

This study focused on three primary objectives to fill the existing research gaps. Firstly, it aimed to develop a scalable methodological framework for identifying and estimating the locations where winter cover crops are grown. Secondly, the study utilized this framework to generate new data on cover crop locations, serving as a benchmark for future studies. Lastly, the research aimed to identify and analyze the NDVI time series, spectral characteristics, and temporal patterns of winter cover crops.

This chapter presents a unique and, to some extent an innovative methodology to identify winter cover crops using remote sensing technologies. The study methodology was applied to the MAP ecoregion, achieving a 97.7% mean classification accuracy using a Random Forest (RF) classifier. This study sheds light on the potential of platforms like Google Earth Engine (GEE) and using Landsat 8 satellite imageries to identify the geographical locations of winter cover crop adoption in the MAP region from 2013 to 2019. This study introduces several novel aspects that set it apart from previous research endeavors. First, it conducts an analysis encompassing a large geographic area, incorporating extensive ground-truthed data. This approach facilitates a more comprehensive understanding of the spatial adoption of winter cover crops. Second, the study utilizes the USDA binary cultivated band and historical noble conservation practice datasets for training the model, enhancing the accuracy and reliability of the obtained results.

These distinctive features of the research contribute to novel insights and advancements in identifying and monitoring winter cover crops using remote sensing techniques.

Accurate mapping of areas with cover crops and those without is essential to provide valuable information to agricultural decision-makers and cost-share providers. The methodology presented in this study has the potential to be applied and replicated in different agricultural regions, given the availability of high-quality training data. By combining sensor sources and ground-truthed data, this study has demonstrated the feasibility of achieving cover crop and non-cover crop classifications with comparable detail in class labels for extensive areas, multiple years, and uniform landscapes, such as the MAP study area. This approach can be adapted for other regions enabling accurate identification and mapping of cover crop adoption. The availability of this data can contribute to formulating policies that are advantageous for producers, while promoting the preservation or improvement of environmental resources and services.

Finally, chapter three, titled "Evaluation of Voluntary Adoption of Cover Crops and Associated Crop Rotations Using Remote Sensing" adopted the model-predicted winter cover crop location data generated using remote sensing technologies, USDA-NRCS government-subsidized cover crop acreage data by county, and the USDA CDL data layer to examines and identify the voluntary adoption of winter cover crops and the associated cropping patterns in the Arkansas portion of the MAP region.

Winter cover crops play a vital role in agriculture by providing various benefits, such as preserving soil health, preventing erosion, and enhancing nutrient retention in fields during the off-season (Adetunji et al., 2020; Basche et al., 2016; Dabney et al., 2001). In the specific context of the MAP region, these crops offer long-term advantages to producers by improving soil structure, increasing soil organic matter, and reducing nutrient losses through leaching or runoff (Aryal et al., 2018; Kladivko et al., 2014). The cropping rotations utilized by producers before and after the adoption of winter cover crops are of great significance in policy research and agricultural planning. Farmers in the MAP region employ various management techniques for cover crops, including crop rotation. The decision-making process regarding cropping plans and rotations is influenced by factors such as the previous crop grown and the subsequent crop to be planted (Dury et al., 2012). Cash crops in many parts of the MAP region are rotated to enhance soil health and manage farm pests (Bergtold et al., 2019). Cash crops such as corn and soybeans are among the major crops alternated in these rotations (Boryan et al., 2014). Previous research on cropping patterns has predominantly concentrated on major cash crops, overlooking the specific identification of winter cover crops (Ambinakudige & Intsiful, 2020; Boryan et al., 2014). This narrow focus can be attributed to researchers' challenges in accurately identifying cover crop areas and effectively incorporating them into existing rotations (Fageria et al., 2005). This has resulted in significant research gaps within the existing literature.

Recently, there has been a significant increase in the adoption of winter cover crops in the MAP region, driven by the notable benefits they offer (Geosolutions et al., 2019). The availability of cost-shared funding from USDA-NRCS programs like EQIP and CSP has particularly stimulated this adoption surge. Consequently, there has been a 50% rise in the reported area dedicated to cover crop planting across the United States from 2012 to 2017 (Wallander et al., 2021). Many producers also voluntarily adopt certain practices, such as cover cropping and no-tillage, independent of funding from CSP and EQIP (Dunn et al., 2016). However, the extent of voluntary cover crop adoption at the county level remains unknown due to challenges in acquiring accurate spatial data and lacking a reliable method for identifying voluntary adoption independent of government cost-shared funding. More importantly, there is a notable research gap in the United States regarding voluntary adoption, as no prior studies have been conducted on this subject. Most of the previous cropping pattern research has been done only focusing on major cash crops without identifying winter cover crops (Ambinakudige & Intsiful, 2020; Boryan et al., 2014).

To address these knowledge gaps, this research aims to accomplish two primary research objectives. First, it seeks to determine the county-wide voluntary adoption of cover crops within the MAP region. Secondly, it intends to analyze the cropping patterns before and after the adoption of cover crops. Additionally, the study aims to examine the complete cropping sequence, specifically focusing on the placement of cover crops versus non-cover crops between cash crops.

This study utilized remote sensing technologies to achieve the first objective, specifically leveraging the GEE platform and Landsat 8 satellite imagery. These tools were employed to identify the locations of winter cover crops in the MAP region from 2013 to 2019. The model-predicted cover crop acres consisted of both government-subsidized and voluntary adoption of cover crops. A subtraction method was applied to distinguish voluntary adoption by deducting the government-subsidized cover crop row sum acres from the model-predicted cover crop row sum acres by county. This approach allowed for the preparation of yearly county-wide maps highlighting the areas where cover crops were voluntarily adopted.

To achieve the second objective, this study focuses on three different cropping patterns revolving around cash crops and their sequential cultivation following cover and non-cover crops. These patterns include (1) finding out which cash crops are planted before cover crops, (2) identifying which cash crops follow cover crops, and (3) mapping out a full one-year cropping pattern that starts with cash crops and incorporates cover and non-cover crops the same year and ends with the reintroduction of cash crops the year after.

This study addresses a significant research gap by providing, for the first time, valuable insights into the county-level voluntary adoption of cover crops and cropping patterns within the MAP region. This understanding of shifting cropping patterns, particularly the increasing adoption of cover crops, is of importance for stakeholders and policymakers in formulating strategies for resilient and sustainable agriculture. These findings contribute to the knowledge base required for promoting agricultural practices that effectively balance productivity and environmental stewardship.

The underlying thread that connects the three chapters of this dissertation is a shared emphasis on the crucial need for sustainable farming practices. These practices must strike a balance between agriculture's ecological necessities and economic realities. Central to the discussions in this dissertation is the role of winter cover crops in maintaining soil health and, as a result, ensuring agricultural productivity. It underscores the need to comprehend producers' decision-making processes to enhance the adoption of these sustainable practices. Recognizing and acting upon these links is vital to the future of agriculture, especially amidst escalating environmental stressors and growing demand for food.

Highlighting the advantages of technology in agriculture, the dissertation brings attention to the potential of remote sensing technologies. These advanced tools provide an efficient and accurate means to monitor agricultural practices, offering invaluable insights into crop management on a broad scale. By leveraging remote sensing technologies, researchers can identify winter cover crop areas, areas of voluntary cover crop adoption and analyze cropping patterns, contributing to a better understanding of the factors influencing farmers' decision-making processes.

In conclusion, this dissertation offers a thorough examination of the adoption of winter cover crops in Arkansas portion of the MAP region. It investigates their role in enhancing soil health and affecting crop productivity. The insights gathered from this study will prove beneficial to policymakers, researchers, and agricultural stakeholders. It contributes to the ongoing dialogue on sustainable agriculture and provides actionable strategies for soil preservation, improved crop productivity, and securing our future in a rapidly evolving world.

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CHAPTER 2: AN EXAMINATION OF THEMATIC RESEARCH, DEVELOPMENT, AND TRENDS IN REMOTE SENSING APPLIED TO CONSERVATION AGRICULTURE

Abstract

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.

Keywords: Remote sensing, Conservation agriculture, Classification algorithm, Spatial resolution, Satellite, Spectral indices, PRISMA

2.1 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 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; R. 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; S. Yang et al., 2021), assessment of soil moisture (Aboutalebi et al., 2019; X. 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; H. 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 (G. Yang et al., 2017; Q. Yang et al., 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 (C. 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; Z. Chen & Wang, 2010; Chughtai et al., 2021; Fonji & Taff, 2014), crop identification and mapping (Belgiu & Csillik, 2018; Xun et al., 2021; S. Yan et al., 2021), phenology mapping using time series (R. Li et al., 2021; Schreier et al., 2021; F. 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., 2021a; 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., 2021a), 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., 2021a; Seifert et al., 2019), regression models (Thieme et al., 2020a; 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; J. 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; Y. 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; Y. 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.

2.2 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; K. L. 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.

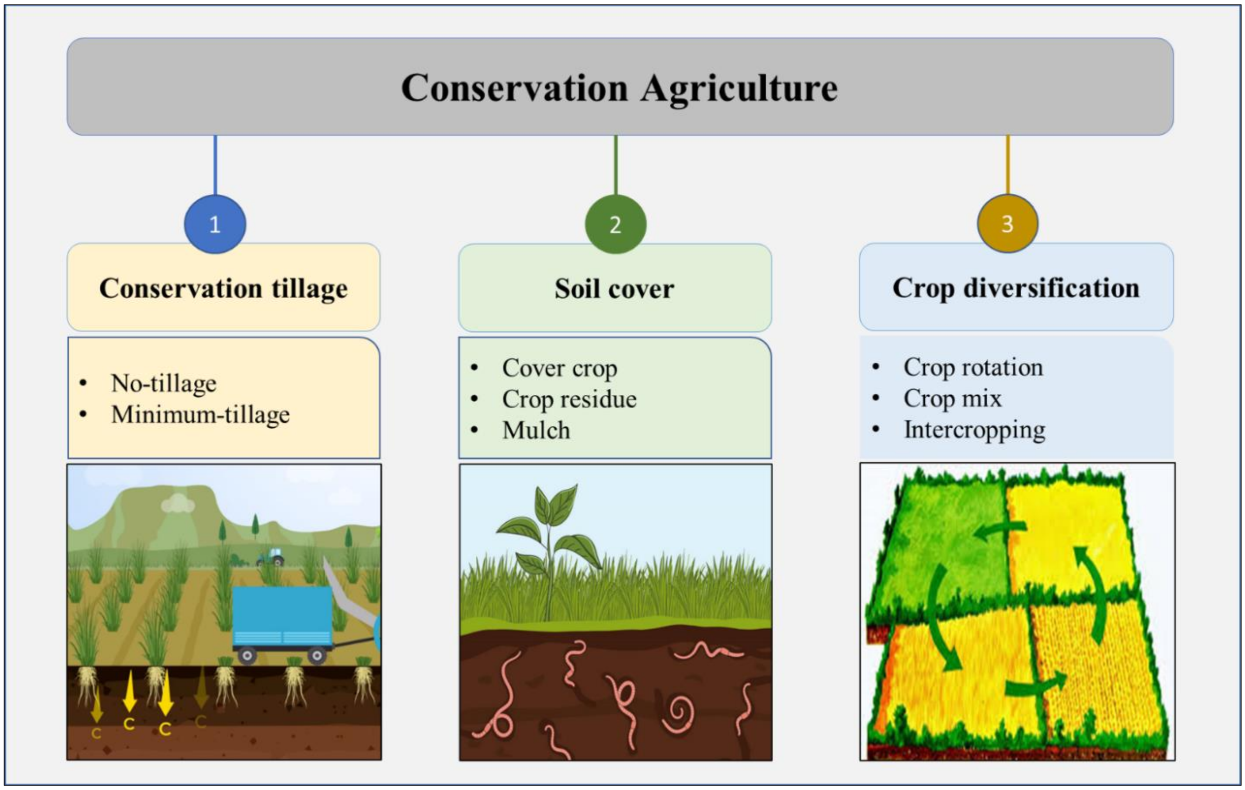

Fig. 1. Three principles of conservation agriculture (Sources: panel 1: https://bit.ly/35cE4x0, panel 2: https://bit.ly/3AuxZYo, panel 3: https://bit.ly/3rHYSEb)

2.3 Materials and methods

2.3.1. 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 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	conservation cover
satellite image*	crop residue
	tillage*
	no-till
	crop rotation
	mulch*
	soil conservation
	soil cover
	multi-cropping
	buffer strips
	contour buffer
	strips
	contour farming
	intercropping
	cropping pattern

2.3.2. Preferred Reporting Items Systematic Reviews and Meta-Analyses (PRISMA)

The PRISMA methodology and protocol framework version 2020 was used in this current work (M. J. 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 (M. J. 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).

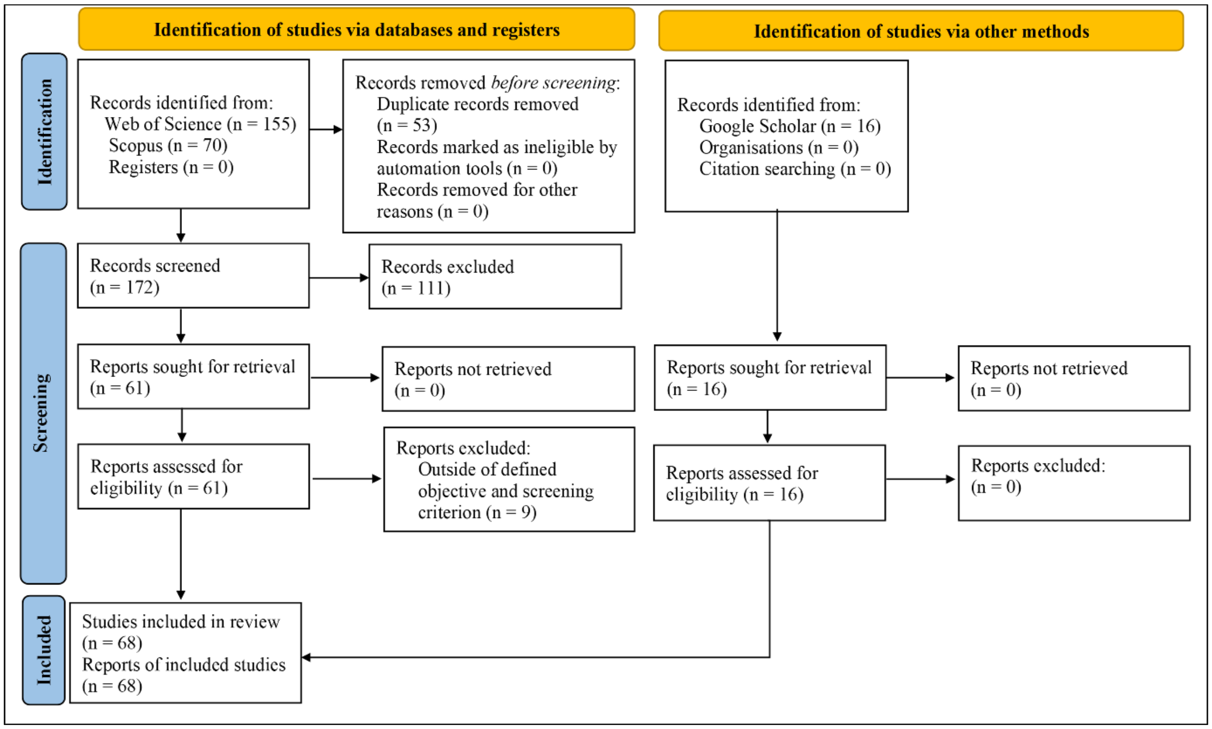

Fig. 2. PRISMA 2020 flow diagram for the systematic review of remote sensing for conservation agriculture [adapted from Page et al. (2021)].

2.3.3. 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. 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.

2.3.4. 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.

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

Table 2 (Cont.)

Number	Attribute	Type	Key categories/description
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

2.4 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.

2.4.1. 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.

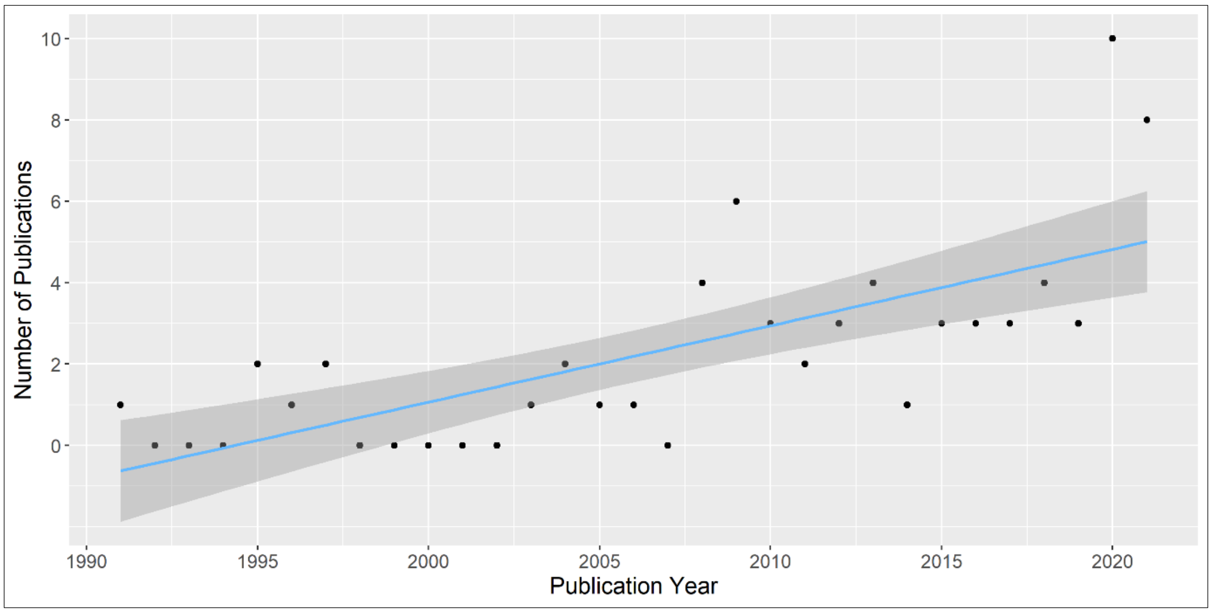

Fig. 3. Number of conservation agriculture papers published per year using remote sensing from 1991 to 2021. [Blue line represents the trend line, and the gray-shaded area represents the 95% confidence interval]

2.4.2. 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.

2.4.3. 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).

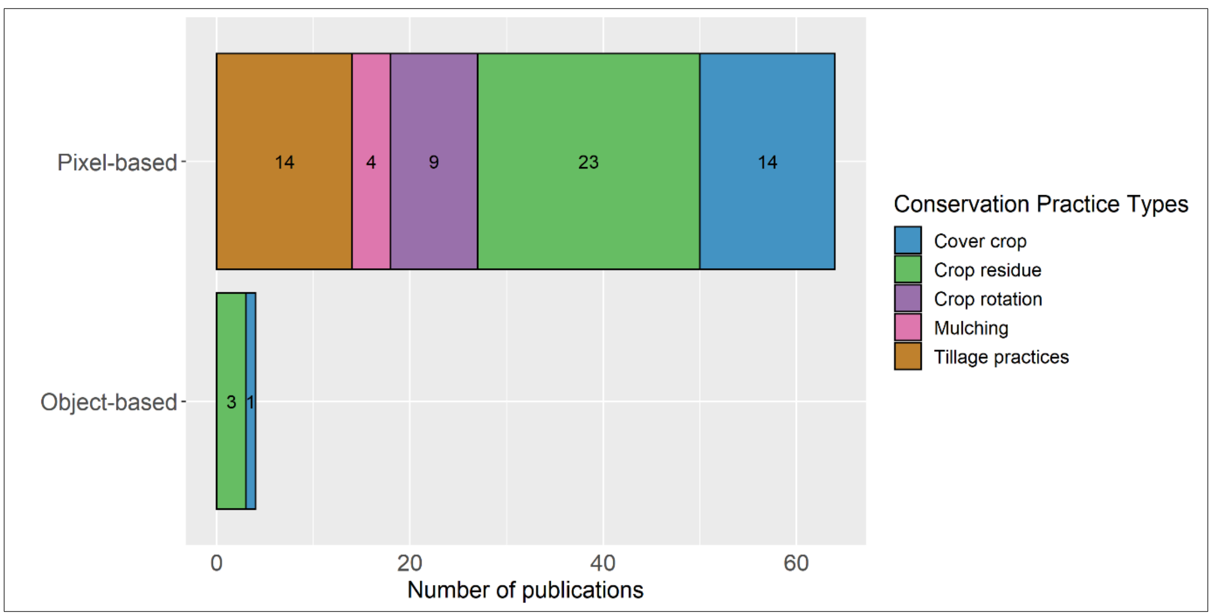

Fig. 4. Conservation practices and classification methods from 1991 to 2021.

2.4.4. 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.

2.4.5. 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 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.

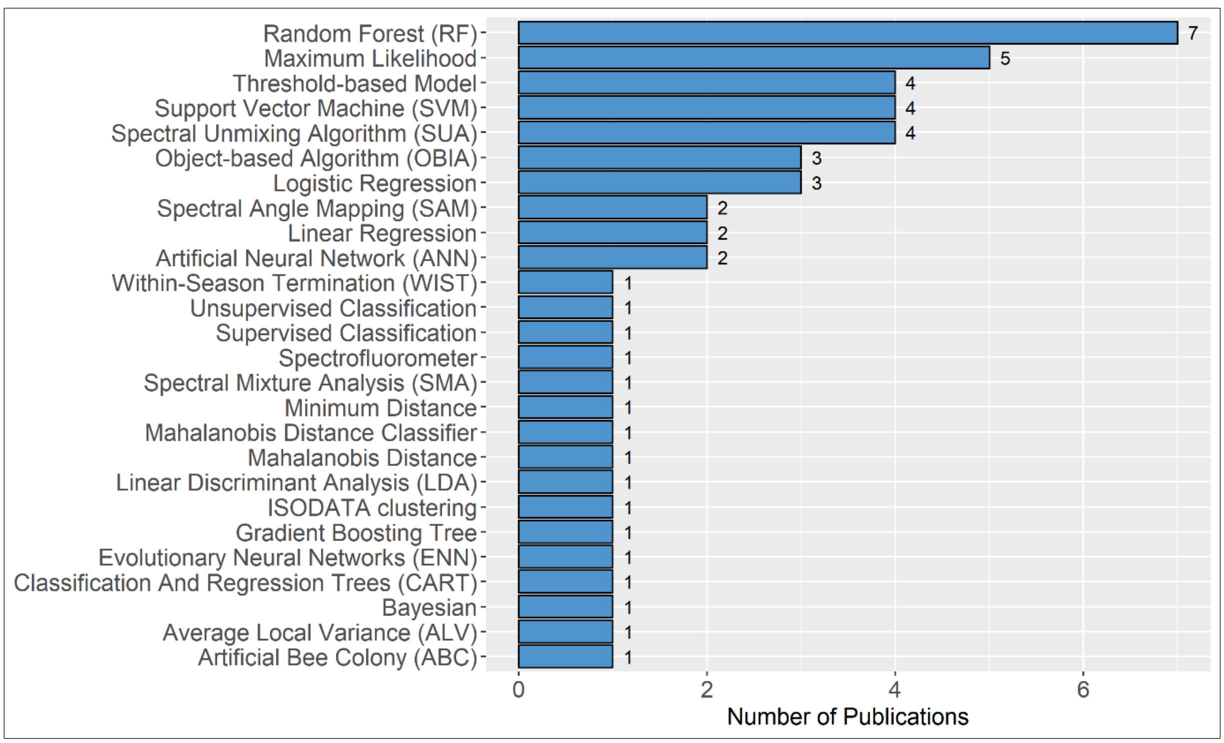

Fig. 5. Conservation agriculture papers by classification algorithm types from 1991 to 2021.

2.4.6. 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.

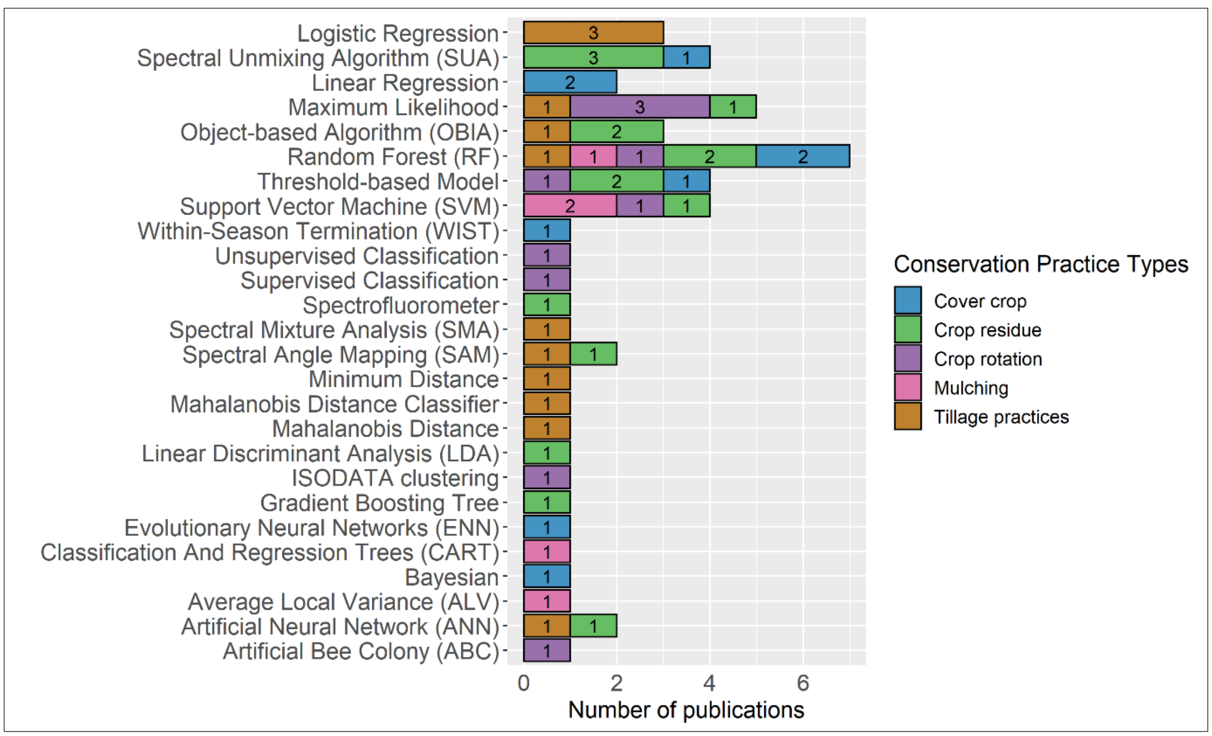

Fig. 6. Conservation practices and classification algorithm from 1991 to 2021.

2.4.7. 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.

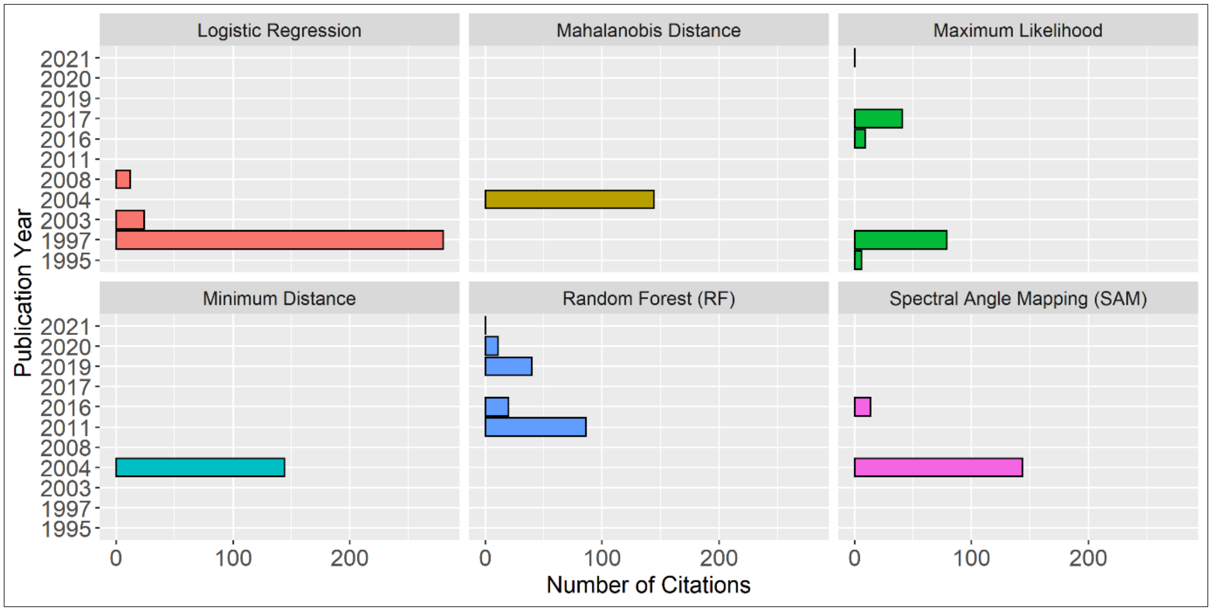

Fig 7. Conservation agriculture papers citations by years grouped by classification algorithm type from 1991 to 2021.

2.4.8. 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 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%.

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

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

Table 3 (Cont.)

Classification algorithm type	Mean accuracy (%)	Accuracy range (%)	Number of articles
Artificial Neural Network (ANN)	73	-	1
Spectral Unmixing Algorithm (SUA)	65	-	1

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

2.4.9. 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%).

2.4.10. 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.

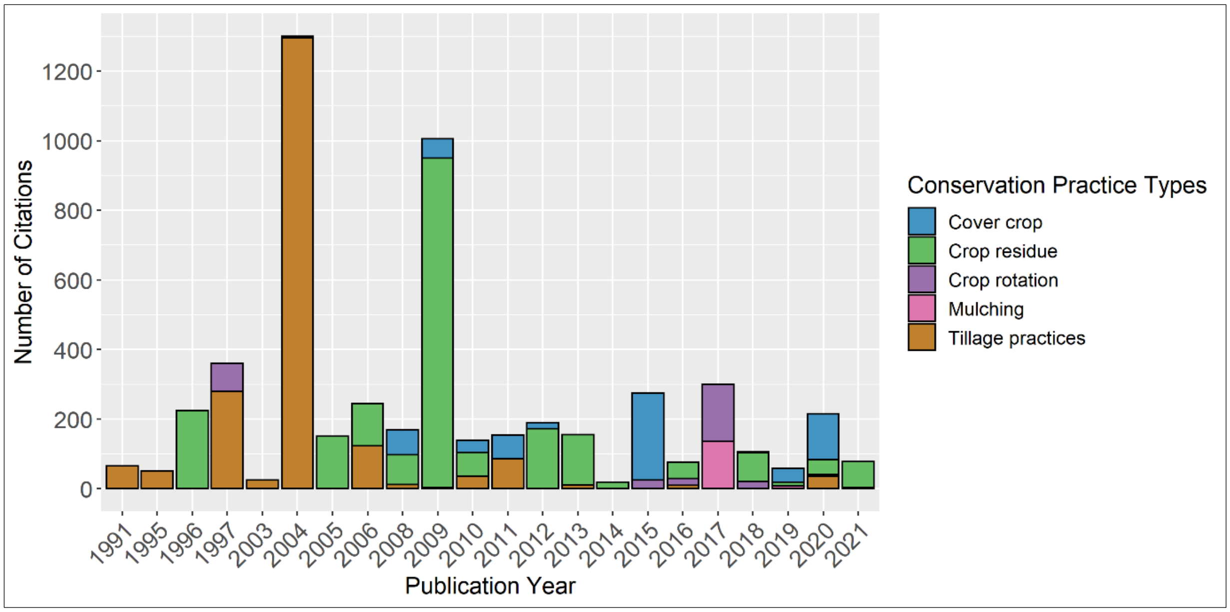

Fig. 8. Conservation agriculture papers citations by years grouped by conservation practice type from 1991 to 2021.

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

2.4.12. 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.

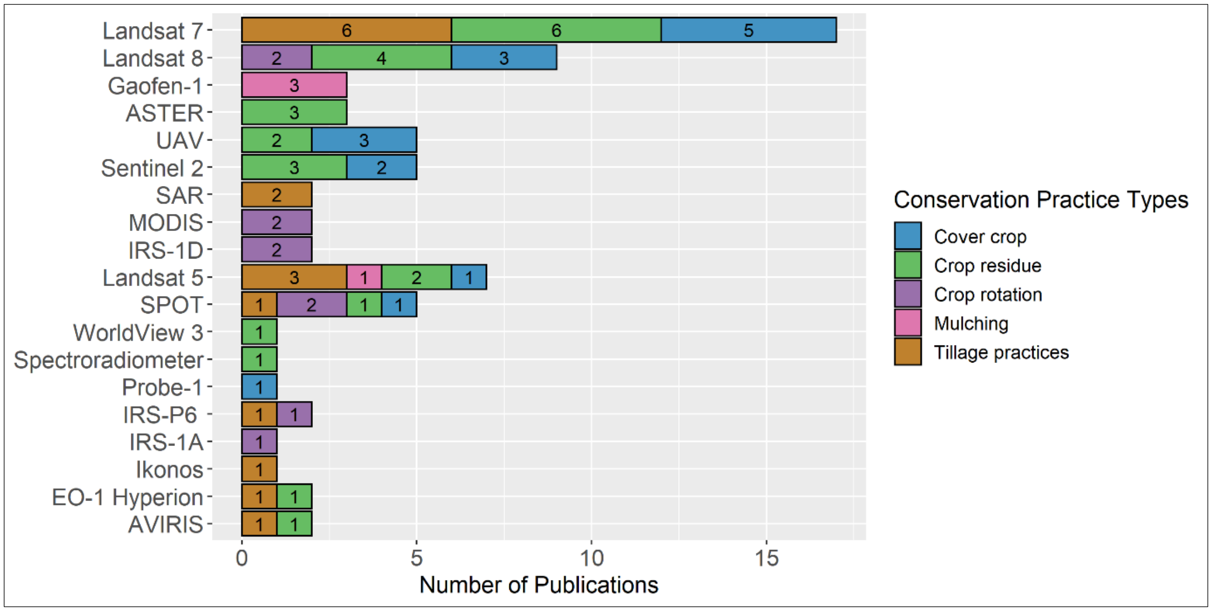

Fig. 9. Conservation agriculture and sensor/satellite type from 1991 to 2021. [ASTER: Advanced Spaceborne Thermal Emission and Reflection Radiometer; UAV: Unoccupied Aerial Vehicle; IRS: Indian Remote Sensing; SPOT: Satellite Pour l'Observation de la Terre; SAR: Synthetic Aperture Radar; MODIS: Moderate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

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.

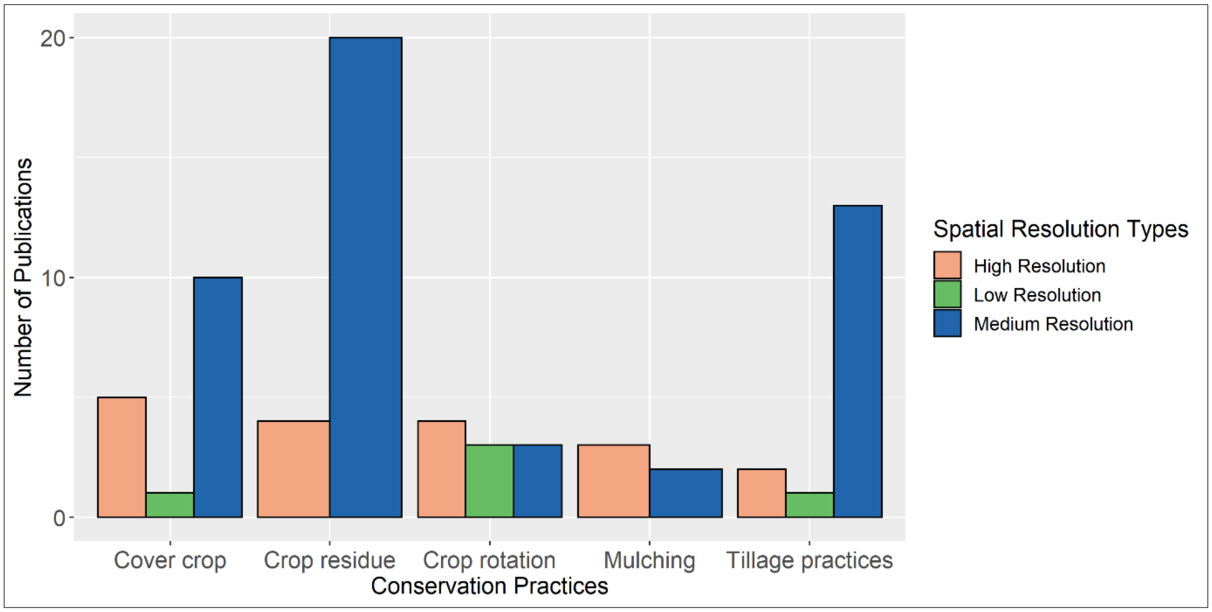

Fig. 10. Conservation agriculture and spatial resolution by practice from 1991 to 2021. [Note: Spatial resolution (pixel size in meters along one dimension): High: > 0 to < 10; Medium: ≥ 10 to ≤ 30; Low: > 30 to ≤ 1000]

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%).

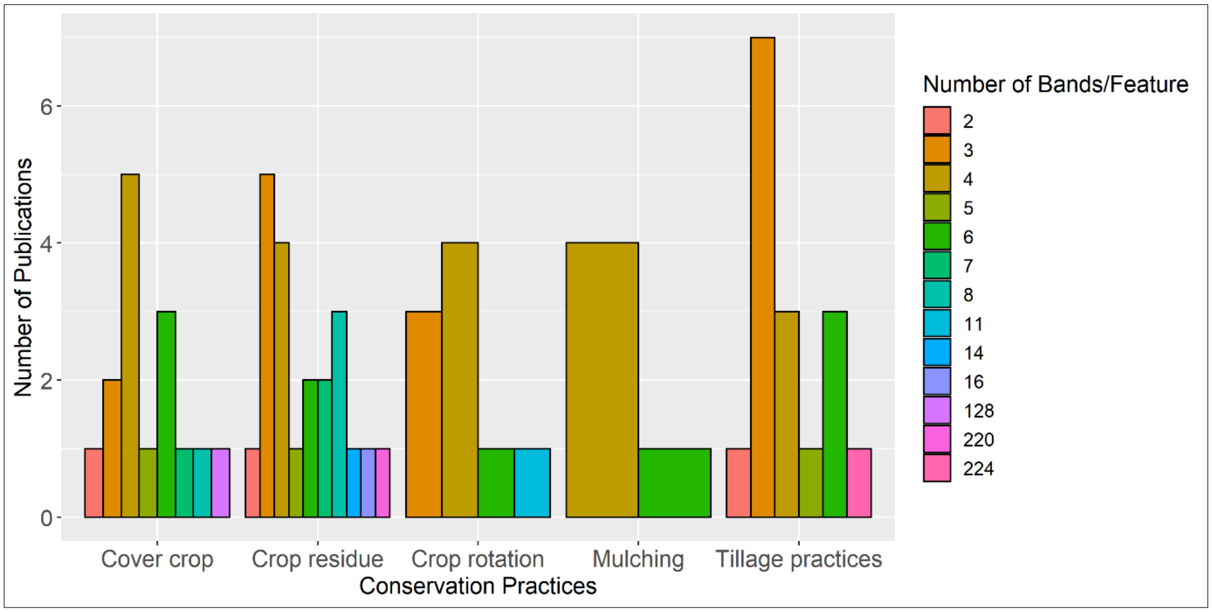

Fig. 11. The number of bands used by conservation agriculture practices from 1991 to 2021.

2.4.13. 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.

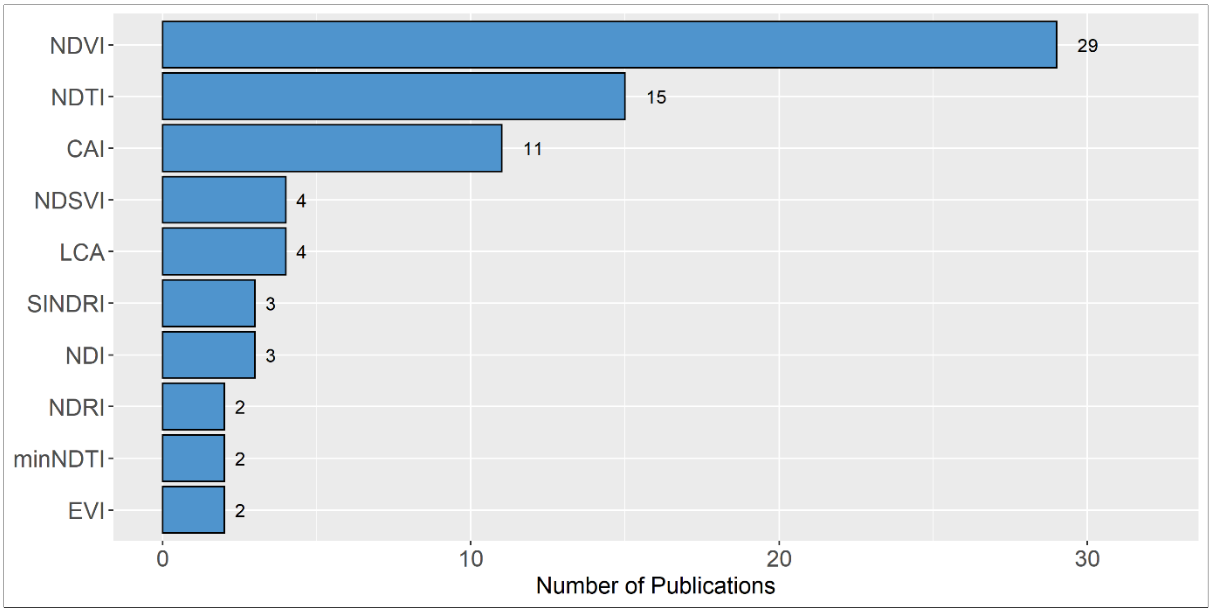

Fig. 12. Top 10 indices found in conservation agriculture publications from 1991 to 2021. [Note: NDVI: Normalized Difference Vegetation Index; NDTI: Normalized Difference Tillage Index; CAI: Cellulose Absorption Index; NDSVI: Normalized Difference Senescent Vegetation Index; LCA: Lignin-Cellulose Absorption 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]

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.

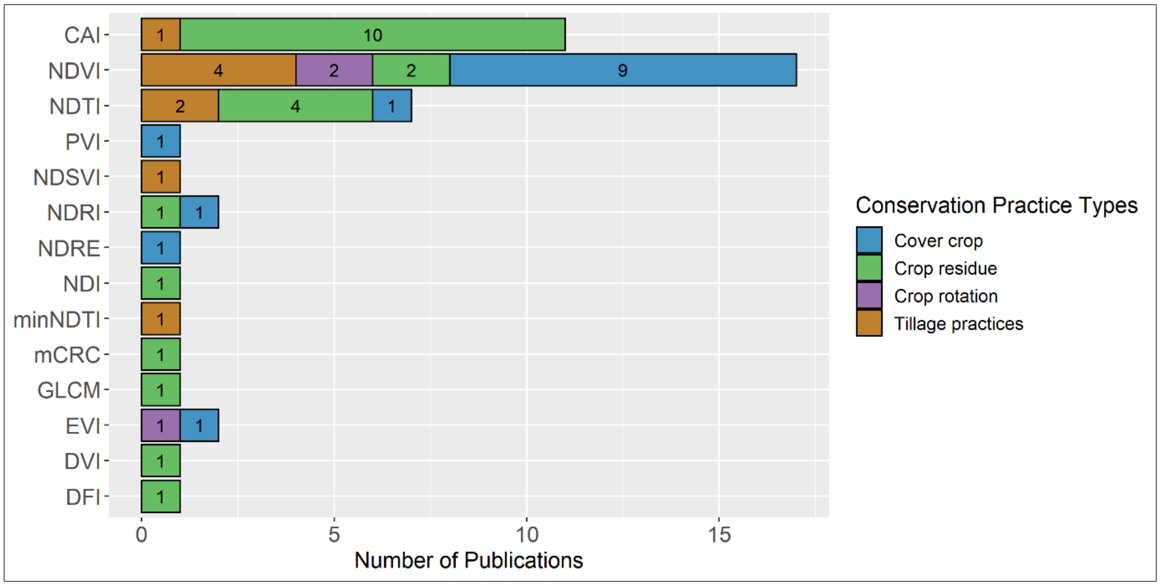

Fig. 13. Top 10 indices grouped by conservation practices from 1991 to 2021.

2.4.14. 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.

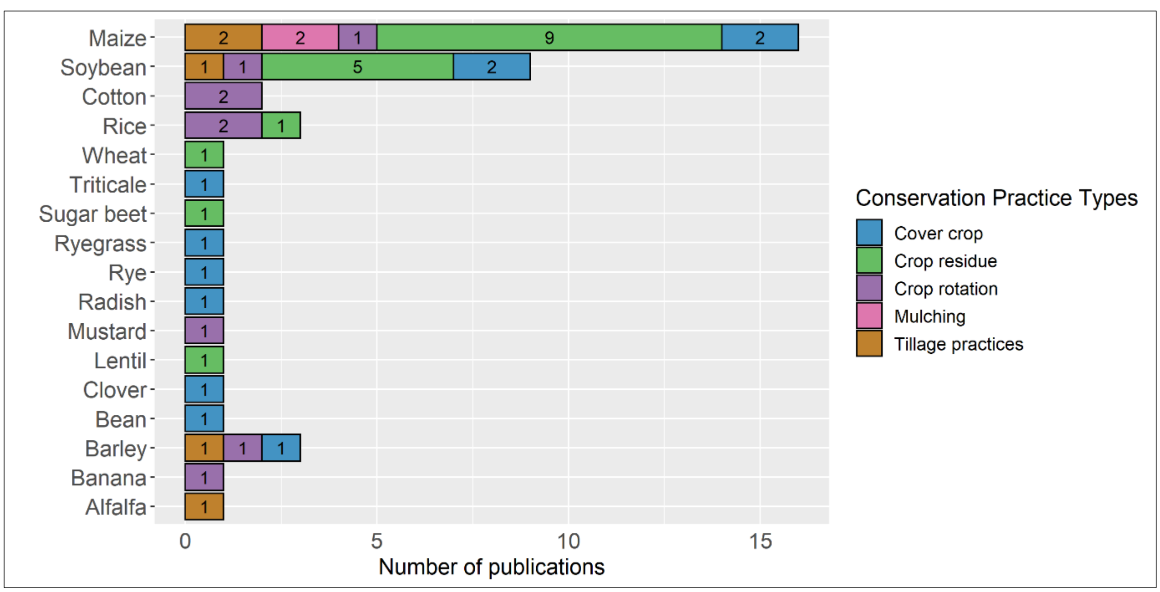

Fig. 14. Conservation practices and crop types from 1991 to 2021.

2.5 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, et al., 2017; Hasituya et al., 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, et al., 2017; Hasituya et al., 2020).

Among the optical data, Landsat 7 and Landsat 8 platforms were popular in crop residue (Barnes et al., 2021a; Chi & Crawford, 2014; Laamrani et al., 2020; Najafi et al., 2018; Pacheco & McNairn, 2010; Sonmez & Slater, 2016a; Zheng, Campbell, Shao, et al., 2013; Zheng et al., 2012), tillage practices (Gowda et al., 2008; Hagen et al., 2020a; South et al., 2004; Sudheer et al., 2010; Watts et al., 2011; Zheng, Campbell, Shao, et al., 2013), and cover crop (Hively et al., 2015a, 2020; Seifert et al., 2019; Thieme et al., 2020a; M. Xu et al., 2018) conservation practices. In contrast, Landsat-5 and the Gaofen-1 platforms were popular in mulching conservation practice (Hasituya, Chen, Li, et al., 2017; Hasituya, Chen, Wang, et al., 2017;

Hasituya et al., 2020; Xiong et al., 2019), while fewer studies used UAVs (Brooker et al., 2021; Cruz-Ramírez et al., 2012; E. R. 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 remote sensing tools and techniques has been increasing (Crowley and 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., 2020a; Hively et al., 2019; Kc et al., 2021a; Leek & Solberg, 1995; Nowak et al., 2021; Serbin, Daughtry, Hunt, Brown, et al., 2009; Serbin, Daughtry, Hunt, Reeves, et al., 2009; Serbin, Hunt, et al., 2009; Thieme et al., 2020a; 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; J. 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, Daughtry, Hunt, Brown, et al., 2009; Serbin, Daughtry, Hunt, Reeves, et al., 2009; Serbin, Hunt, et al., 2009; Zheng et al., 2012), tillage practice (Beeson et al., 2020; Gowda et al., 2008; Hagen et al., 2020a; Leek & Solberg, 1995; Sonmez & Slater, 2016a; Sudheer et al., 2010; Watts et al., 2011; Zheng, Campbell, Shao, et al., 2013), and cover crop (Gao et al., 2020; Hively et al., 2015a, 2020; E. R. Hunt et al., 2011; Kc et al., 2021a; Seifert et al., 2019; Thieme et al., 2020a; 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, 2015a, 2020; Prabhakara et al., 2015a), four studies (Conrad et al., 2016; J. Liu et al., 2018; Manjunath et al., 2015; Waldhoff et al., 2017) and three studies (Hasituya, Chen, Li, et al., 2017; Hasituya et al., 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., 2021a; Chi & Crawford, 2014; Dvorakova et al., 2020; Serbin, Hunt, et al., 2009; Sonmez & Slater, 2016a) and tillage conservation studies (Beeson et al., 2020; Brisco et al., 1991; Gowda et al., 2008; Hagen et al., 2020a; Smith et al., 1995; Zheng, Campbell, Shao, et al., 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, Daughtry, Hunt, Brown, et al., 2009; Serbin, Daughtry, Hunt, Reeves, et al., 2009; D. 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 (D. 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., 2020a; Hively et al., 2018; E. R. 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., 2020a; 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., 2021a; Beeson et al., 2016; Hively et al., 2018), cover crop (Hively et al., 2015a; Kc et al., 2021a; Seifert et al., 2019; Thieme et al., 2020a) 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, et al., 2017; Hasituya et al., 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 (D. Liu & Xia, 2010). Furthermore, in a few articles, some researchers have used rule-based classification techniques (J. 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., 2021a; Conrad et al., 2016; Hasituya et al., 2020; Kc et al., 2021a; Seifert et al., 2019; Watts et al., 2011; Yue & Tian, 2020), Gradient Boosting Tree (Hively et al., 2019), Support Vector Machine (Hasituya, Chen, Li, et al., 2017; Hasituya, Chen, Wang, et al., 2017; Najafi et al., 2021; Waldhoff et al., 2017), Object-based Algorithm (Najafi et al., 2018, 2021;

Zheng, Campbell, Shao, et al., 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, et al., 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., 2021a; Hively et al., 2009, 2020; Kc et al., 2021a; 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, Daughtry, Hunt, Brown, et al., 2009; Yue & Tian, 2020; Zheng et al., 2012) and the CAI (Dvorakova et al., 2020; Zheng, Campbell, Serbin, et al., 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.

2.6 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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CHAPTER 3: WINTER COVER CROP IDENTIFICATION: A REMOTE SENSING-BASED METHODOLOGICAL FRAMEWORK FOR NEW AND RAPID DATA GENERATION

Abstract

Accurately identifying and systematically mapping winter cover crops and their phenological characteristics offer significant benefits to agricultural producers and policymakers, as cover crops are a potential solution to climate change mitigation. We present a methodological framework for identifying and mapping the presence of winter cover crops at the field level and finally aggregated to county scales from 2013 to 2019 by using the Google Earth Engine (GEE), a random forest classifier with time series data from Landsat 8, and yearly cover crop training data from the United States Department of Agriculture (USDA)- Natural Resources Conservation Service (NRCS). The methodology was tested with data from the Mississippi Alluvial Plain (MAP) region. Despite the inter-annual agronomic and climatic variations across space, results demonstrate an overall mean classification accuracy of 97.7%, with a Kappa coefficient of 0.94. Results also revealed a 34% increase in model-predicted cover crop adoption in the study region from 2013 to 2019. Additionally, we demonstrated how to use a multi-year dataset to efficiently map the length of the growing season and winter cover and non-cover phenological characteristics using the Normalized Difference Vegetation Index (NDVI) time series, spectral signature, and temporal profile analysis. We observed that spectral bands and other spectral indices assist with distinguishing between cover and non-cover crop areas. The methodology developed and tested has broad applicability to other regions where cover crops have been promoted for climate-change mitigation and improving soil health for long-term sustainability.
Keywords: Winter cover crops, remote sensing, methodological framework, Random Forest classifier, Google Earth Engine, Landsat

3.1 Introduction

Cover crops are a management practice that can sustainably enhance crop yields while benefiting soil health and water quality (Basche et al., 2016). Cover crops are typically planted in the fall after cash-crop harvest and provide a vegetative soil cover during winter. Previous literature has classified cover crops as providing environmental services to producers in the form of soil erosion control, improved water infiltration, reduced runoff, reduced weed and insect pressure, reduced leaching of chemicals from agricultural fields, and increased healthy soil microbial activity (Basche et al., 2016; Cassman et al., 2002; Dabney et al., 2001; Singer et al., 2011). While the adoption of cover crops is not a new agricultural practice in the United States, its wide range of environmental and economic benefits has recently drawn the attention of producers and policymakers as a part of their holistic soil and water conservation approach (Sarrantonio & Gallandt, 2003). The Natural Resources Conservation Service (NRCS) of the United States Department of Agriculture (USDA) and 50 state organizations have provided financial incentives to farmers for growing cover crops in their fields. The incentive programs, such as the Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP), aim to promote conservation and sustainable agriculture practices. As a result, the reported area planted with cover crops in the United States increased by 50 % from 2012 to 2017 (Wallander et al., 2021). Cover crop adoption rates were collected from the USDA's Census of Agriculture and the Agricultural Resource Management Survey, with field-level data obtained from Production Practice and Cost Report surveys (Wallander et al., 2021).

Although government incentives to encourage producers to adopt cover crops have considerably expanded in funding from 2012 (Wallander et al., 2021), it is still geographically unclear exactly where the cover crops are being adopted because there is a lack of ground-truthed, spatial data, and a reliable method to identify cover crop locations. One of the primary methods of conducting historical research to identify cover crop adoption has been through field-based research and surveys of farmers (Wallander et al., 2021). The approaches of field-based research and surveys, while having unique benefits, face challenges in aggregating data across large geographic areas. These methods can be costly, time-consuming, and labor-intensive and may not provide a complete picture of spatial adoption for informing policy decisions. Further, measurement error, human error during the recording process, and the nature of small, localized datasets hinder external validity. Given the development of new remote sensing tools and techniques, researchers can conduct a range of field-based or large-area research projects rapidly, often at minimal cost, and with minimal labor to improve overall data accuracy. Like traditional study techniques, remote sensing techniques have their drawbacks. Limited temporal and spatial resolution, local cloudiness, and image gaps can make classifying vegetation difficult (Al-Wassai & Kalyankar, 2013). The advantages of remote sensing, in terms of timeliness and cost, can outweigh existing limitations when policymakers require large areas to be analyzed, even when there are significant data gaps.

The development of satellite technology offers vast collections of remotely sensed data for analysis in various sectors such as agriculture, environmental and disaster management, navigation, and transportation. Due to its relative ease of use, remotely sensed data have gained widespread adoption throughout the agricultural sector. The development of multispectral sensors, such as those with 3 to 10 wide bands, and hyperspectral sensors, such as those with hundreds of narrow bands, has made it possible to implement them on a variety of satellite platforms, including Landsat, Sentinel, as well as Unmanned Aerial Vehicles (UAVs), for Earth observation research projects. As a result, we can now monitor agricultural land surfaces' spectral and temporal characteristics with relative ease and at high spatial and temporal resolution. The lack of data within a specific temporal and geographical range is reduced by using many satellites. However, to use fine spatial resolution imagery (Sentinel), one must forgo high temporal resolution imagery (Landsat) and vice versa.

Conservationists face two challenging issues: estimating where and what the total area of cover crops is in the United States. Estimating crop phenology responses (refers to the timing of various crop growth stages, such as emergence, vegetative growth, flowering, and maturity) and identifying cover crop areas are possible through analyzing remote sensing data in conjunction with the United States Department of Agriculture (USDA) cropland data using multimodal methods, such as fusing multi-source data and image fusion. However, variations in spatial, temporal, and spectral resolution make it difficult to combine data from several platforms (Gao et al., 2009; Masek et al., 2018; Sadeh et al., 2021; Teillet et al., 2001). Nonetheless, a multimodal image fusion method or fusing multi-source data may be beneficial for distinguishing between cover crops and cash crops and can be accomplished using advancements in big-data platforms, such as the Google Earth Engine (GEE) (Gorelick et al., 2017). As a result, crop identification has improved dramatically, even in heterogeneous landscapes, such as the Mississippi Alluvial Plain (Dewitz & USGS, 2021; Peña-Barragán et al., 2011).

Previous studies have used several satellite imageries and spectral and vegetation indices to identify, comprehend, categorize, monitor, and evaluate winter cover crops at various geographic scales (Kc et al., 2021; Hively et al., 2015; Seifert et al., 2018; Hagen et al., 2020; Rundquist & Carlson, 2017; Thieme et al., 2020). However, studies on cover crop identification and monitoring used remote sensing techniques limited to small areas, with geographic scales ranging from a few acres to a few hundred acres. Studies of larger areas with ground truthing are sparse or rely on error-prone windshield surveys with low GPS accuracy. Few studies used the USDA cropland band's maize and soybean pixels, and none used the USDA binary cultivated band or the USDA-NRCS historical noble conservation practice datasets for cover crop model training. Using images acquired by Landsat satellites between 2008 and 2019 on the GEE platform, Kc et al. (2021) evaluated the geographic and temporal inventory of winter cover crops grown in a maize-soybean rotation in the Maumee River watershed spanning Ohio, Indiana, and Michigan. In another study, Hively et al. (2015) evaluated the presence and amount of green winter vegetation on agricultural fields in four counties in Pennsylvania (i.e., Berks, Lebanon, Lancaster, and York) from 2010 to 2013 using Landsat and SPOT satellite imagery in conjunction with the USDA Cropland Data Layer (CDL). Similarly, using publicly accessible Landsat satellite data from 2008 to 2016, Seifert et al. (2018) investigated regional and temporal patterns in cover crop occurrence in maize and soybean fields in eight midwestern states using a single image composite during the winter season.

The advantages of using a single image composite for large-area research are that they average out the crop spectral reflectance over a growing season, and limited ground-truthed data are needed for classification. While this helps identify whether a field is planted with cover crops, it is difficult to account for the temporal variability in cover crop phenology due to many factors, such as weather, management practices, and field conditions (Kc et al., 2021b). Hagen et al. (2020) used a Normalized Difference Vegetation Index (NDVI) time series along with a NDVI threshold value to estimate whether individual pixels (30 m in size) did or did not have a winter cover crop. Similarly, Rundquist & Carlson (2017) used NDVI generated from Landsat 8 satellite data and a NDVI threshold value to assess the emergence of cover crops in maize and soybean fields. In this study, they only included fields with more than 10 acres (4.05 hectares) of vegetation as cover crop fields. Thieme et al. (2020) used linear regression between satellite vegetation indices and USGS/USDA-ARS field sample data obtained on Maryland farms between 2006 and 2012 to measure cover crop growth. Their study reported significant relationships between the observed percentage of vegetative ground cover and the natural logarithm of cover crop biomass, which was determined from satellite measurements of the NDVI.

The application of remote sensing using GEE has been widely used (Arévalo et al., 2020; Gorelick et al., 2017). Previous research has shown the value of using GEE to classify land use and identify land use changes (Le'an et al., 2021; Phan et al., 2020; Shafizadeh-Moghadam et al., 2021), estimate environmental impacts (Z. Liu et al., 2022; Wang et al., 2022; Y. Yan et al., 2021), and classify crop types (Gumma et al., 2020; Shelestov et al., 2017; Shen et al., 2022). The methodologies used include unsupervised, supervised, rule-based, and/or time series algorithms (Boschetti et al., 2017; Roy & Yan, 2020; Shew & Ghosh, 2019). However, an in-depth literature review suggests that only a limited number of studies have been conducted to detect winter cover crop growing areas using GEE remotely sensed satellite images (Hagen et al., 2020b; Hively et al., 2015b; Kc et al., 2021b; Rundquist & Carlson, 2017; Seifert et al., 2018). Consequently, there is a significant gap in research on mapping winter cover, as previous research used limited ground truthing and often relied on error-prone windshield surveys.

This study presents several novel aspects that distinguish it from previous research. First, we analyze a large geographic area with extensive ground-truthed data, enabling a more comprehensive understanding of the spatial adoption of winter cover crops. Secondly, we used the USDA binary cultivated band and historical noble conservation practice datasets to train our model, enhancing the accuracy and reliability of the results. These unique features of our research provide novel insights and contribute to advancing winter cover crop identification and monitoring using remote sensing techniques by applying the methodology to the Mississippi Alluvial Plain (MAP) ecoregion, an important agricultural region in the United States.

The specific objectives of this research were to (1) develop a scalable methodological framework to identify and estimate winter cover crop growing locations, (2) use the methodological framework to generate new cover crop location data as a benchmark for future cover crop studies, and (3) identify and analyze the NDVI time series, spectral, and temporal profile of winter cover crops for Arkansas's part of MAP study region.

3.2 Materials and methods

3.2.1. Methodology framework for identification of winter cover crop

Our methodological framework was created by merging GEE-derived remote sensing and USDA-NRCS field-level training data to identify and map winter cover crops. In addition, we used NDVI time series, spectral and temporal profiles of cover and non-cover crop areas. The methodology is illustrated as a flow chart in (Fig. 1), further explained in the following sections.

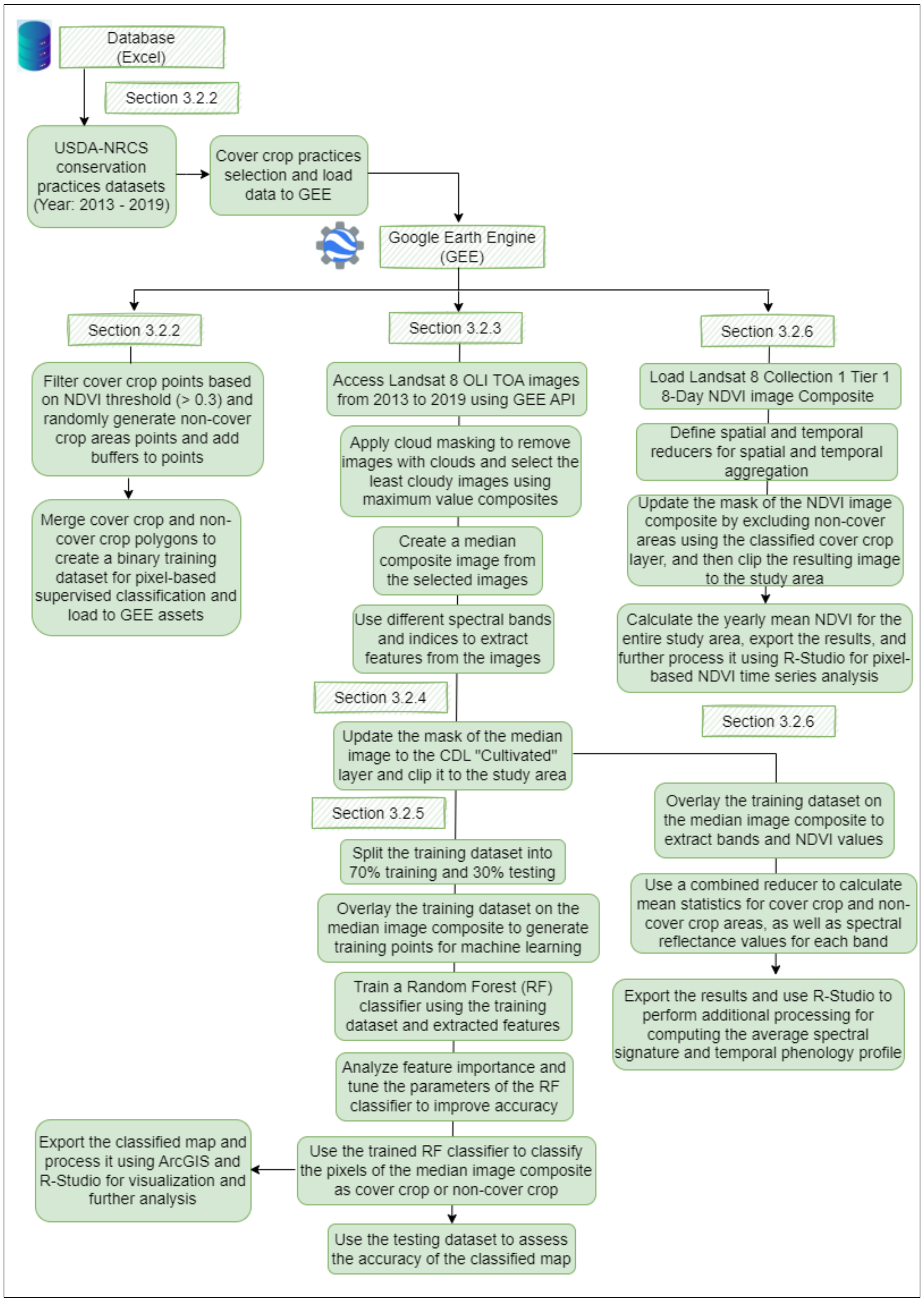

Fig. 1: The methodology workflow framework

3.2.2. Cover crop government data pre-processing

The USDA-NRCS dataset includes cover crops and other conservation practices at a field level planted to different types of cover crops for which the producer received a government funding contract. In this database, a field is defined as an area planted with one type or a mixture of cover crops during a specific year, also known as the applied year. Each field received a single, government-funded contract, and each contract was associated with a GPS coordinate point. The types of cover crops planted under contract were not specified in the NRCS database. As a result, we treated and combined cover crop practice types as a single “cover crop” category and added a 30-m square buffer around each GPS coordinate point to match with the Landsat 8-pixel resolution to increase accuracy following Kc et al. (2021). Cover crop geographical coordinates were used in this study as training data and consisted of observations with spatial coordinates (i.e., longitude and latitude) to represent where each cover crop conservation practice funded by USDA-NRCS took place from 2013 to 2019 (Fig. 1).

One of the limitations of the USDA-NRCS database is that certain cover crop locations lack GPS accuracy. Often, producers would record their GPS location from their home or farm shop instead of the site on their farm where the actual cover crop was being grown. We applied a rule or threshold-based approach for cover crop point data filtering to generate quality training data for cover crop identification using machine learning models (Ghazaryan et al., 2018). Filtering and identifying points within cover crop fields were performed using an NDVI threshold value greater than 0.3. This methodology is similar to what has been done in previous studies (Hively et al., 2015b; Kc et al., 2021b; Thieme et al., 2020b). Using the GEE, cover crops were defined as having an NDVI pixel value greater than 0.3, while the remaining pixels were categorized as “non-cover crop” pixels. Everything else, such as bare soil, farm-built areas, shallow and sparse vegetation (NDVI < 0.3), winter weeds, and some non-green crop residue pixels, may fall under the non-cover crop category. However, since we used the CDL data layer to filter out non-cultivated fields, most non-cover crop pixels were bare soil areas (see section 3.2.4). To cross-check the accuracy of the final training data, we used PlanetScope high spatial resolution (5 m) and near-daily temporal resolution satellite imageries, which only became accessible in 2016 (Planet Team, 2017). This methodology was chosen to randomly cross-check if a cover crop pixel is present at the farm point location of our final training data within the selected temporal month's range. Finally, to feed the machine learning model and learn features from the training data, the final binary training dataset per year was uploaded in GEE Assets, a cloud-based repository for storing and managing large geospatial datasets. For privacy reasons, all personally identifiable information was omitted from the analysis. For subsequent mapping, farm locations were used as training data, and ranges of acres were aggregated to the county as required by USDA-NRCS in data-sharing agreements.

3.2.3. Landsat-8 image pre-processing

The NASA Landsat 8 Operational Land Imager (OLI) Top of Atmosphere (TOA) 30-m spatial and 16-day temporal resolution data products were used to obtain the satellite images for identifying cover crop growing locations across time (Hively et al., 2015b). Our methodology consisted of three parts. First, the method involved selecting the ground cover months for the cover crop; second, removing cloud cover; and finally, identifying the cover crop using a machine learning algorithm with multiple spectral reflectance bands and indices. Winter satellite images were collected for five months (November to March) after the last fall crop harvest and before the emergence of the spring crops to determine the winter cover crop each year from 2013 to 2019. Each selected image is stacked on top of one another to produce the final image composite. The start of the winter cover crop season in November was chosen to reduce the possibility of detecting pixels on the plots of unharvested spring-sown crops, mainly cotton, that may be harvested late in the year. Similarly, the senescence or termination of the winter cover crop was planned for March because certain spring-seeded crops may be planted as early as

March, with seedlings beginning to emerge in April and May. Exploration with shorter or longer periods finalized the temporal selection period to prevent the misclassification of winter cover crop pixels during image classification using the machine learning algorithm.

Cloud coverage is another challenge for crop identification using optical remote sensing. Cloud cover reduces the number of valuable observations during the identification process and creates a misclassification problem since optical satellites cannot penetrate cloud cover, unlike mixed-pixel problems involve multiple classes of nearby objects. Different cloud, cloud shadow, and snow-masking algorithms have been used to eliminate image pixels compromised by different types of clouds (Mateo-García et al., 2018). The correct cloud-masking process selection depends on the research methods used. To create maximum value image collections, when cover crop growth peaks for each cover crop pixel during the growth season (i.e., November to March) for each year from 2013 to 2019, Landsat 8 satellite images with the least amount of cloud cover were sorted using the GEE built-in sort filter function. For cloud-masking of Landsat images in this study, we used the Quality Assessment (QA) band generated through the C Function of Mask (CFMask) algorithm, which is provided with each Landsat image by default (Foga et al., 2017). This QA band helps to remove unnecessary image pixels that contain cloud, cloud shadow, and snow/ice and offers a correct representation of the cover crop vs. non-cover crop signal. Unsigned values representing bit-packed combinations of the surface, atmospheric and sensor conditions are included in each pixel of the QA band. Unsigned values have an impact on a pixel's total value. For instance, the NDVI values calculated over pixels with cloud coverage will not accurately represent the vegetation cover on the ground. If a cloud covers a pixel, it will not receive the same amount of sunlight as a cloud-free pixel, and, as a result, the NDVI value for that pixel will be lower than it would be without cloud coverage. This lower NDVI value may not accurately represent the actual vegetation cover on the ground since the presence of the cloud has influenced it. Similarly, pixels with other types of atmospheric or sensor conditions may also have unusual NDVI values that do not accurately represent the true vegetation cover on the ground. The findings of phenology research would thus not accurately reflect the surface features of seasonal plant development if such pixels were used. Cloud-compromised pixels will result in lower NDVI values, making measurements, like peak maturity or time of green-up, appear to have happened later than they did.

In addition to cloud-masking and maximum value image collection generation, we used different spectral bands and indices to identify winter cover crop growing locations from spectral reflectance. To identify locations of cover crops and non-cover crop areas throughout the chosen timeframe, several Landsat 8 spectral bands and indices were used (see Appendix Table A1). Random Forest (RF), a popular machine learning algorithm, can differentiate between cover and non-cover crop areas using multiple bands and spectral indices. For instance, in the case of cover crop growing areas, it is important to observe the distinct color differences that are visible when cover crops reflect and/or absorb sunlight in the visible (i.e., red, green, and blue) and near-infrared (NIR) bands. This helps identify areas where cover crops thrive and allows for better monitoring of their growth. Crops use solar energy to create biomass by reflecting certain wavelengths and absorbing others. By identifying the presence of chlorophyll pigments in crop leaves, we can determine where vegetation is growing in the fields. During photosynthesis, crop leaves absorb wavelengths in the visible (i.e., blue and red) light spectrum and strongly reflect wavelengths in the green and near-infrared spectra, allowing us to distinguish active growth areas. Furthermore, observing the peak growth and senescence of cover crops provides additional information about the state of the crops and their growth cycles.

Different criteria have been used to identify pixel values over a region or a selected point location. In GEE, reducers aggregate data over time, space, bands, arrays, and other data structures. The class "ee.Reducer" defines the aggregation of data. For the aggregate, the reducers in this class can define a statistic (e.g., minimum, maximum, mean, median, standard deviation, etc.). For instance, all satellite images in our image collection were reduced to a single image using a median reducer. The output is calculated on a pixel-by-pixel basis, with each output pixel comprising the median value of all the collected images at that specific area pixel. Instead of using the maximum composite, we opted for the median composite, eliminating clouds and shadows from image pixels. When the median reducer is used to reduce an image collection, the composite value of each band is the median across time.

The advantage of using a single image composite for a large study region is that the composite averages out winter cover crop spectral reflectance over a cover crop growing season (November to March) and identifies whether a field is planted to cover crops. Nonetheless, the single image composite has some limitations when used to track changes in seasonal crop phenology, which is not the prime focus of this research, but rather the creation of a general framework for identifying whether a field has a cover crop. For instance, contrary to the notion that certain cover crops remain dormant or die due to frost in December and January, they remain green throughout the winter, with active growth increasing in February and March (appendix Fig. A1). This phenomenon, known as 'green-up,' leads to an increase in cover crop biomass, resulting in less visible soil and a greener appearance of the fields due to canopy closure. Regardless of whether a cover crop died during a hard freeze following seedling development or laid dormant before re-greening later, our proposed algorithm can determine whether a field was planted with a cover crop. The presumption is that our methodology can recognize cover crop vegetative signals if they appear inside our defined temporal window. However, our method is only effective for a single growing season (i.e., single bell-shaped growth pattern curve) and cannot distinguish between multiple growing seasons (i.e., more than one bell-shaped growth pattern curve), limiting its ability to identify anomalies from winter frost kills of cover crops. Finally, in this study, after adding various spectral bands and indices to the image collections and removing cloudy imagery, we create a single median image composite using the GEE median reducer (Broich et al., 2011).

3.2.4. Mixed pixel correction using USDA Cropland Data Layer

Mixed pixels can weaken the vegetation signal, making crop mapping challenging (Hively et al., 2015b). A mixed pixel occurs when multiple class values are observed in each area represented by the pixel. Our study aims to determine the binary spectral signature for winter cover crop areas and classify non-cover crop areas. Our methodology provides high precision at the pixel level without needing classes of water regions, developed areas, forest areas, and other land use categories, as this study used the USDA-NASS Cropland Data Layer (CDL) "cultivated" annual layer. This "cultivated" binary layer only provides information on the land areas specifically used for agricultural purposes. The CDL is a crop-specific land use raster layer that is georeferenced annually. Since 2008, a crop cover map for the continental USA has been produced using medium-resolution satellite images, ground-truthed data, and a decision tree-supervised classification. Since the CDL has been using crop-specific pixel-level information at field scale resolution (30 m), it has been used by previous researchers for crop identification (Hao et al., 2020; Q. Li et al., 2015; Momm et al., 2020), assessment of crop rotation and cropping pattern (Plourde et al., 2013; Sahajpal et al., 2014; Stern et al., 2012) and land use change detection (Johnston, 2013; Lark et al., 2015), and many other applications (Lark et al., 2017, 2021). The CDL "cultivated" band has two-pixel values: 1 and 2, which represent ‘non-cultivated’ and ‘cultivated’ lands, respectively. The data for this band is available from 2013 to 2020. In contrast, data are available for the CDL "cropland" band, which consists of crop and land use-specific bands (i.e., value ranges from 1-254) from 1997 to 2020. Except for a few crops like winter wheat (Triticum aestivum L.), there is little specific information about winter cover crops present in "cropland" bands. We selected CDL "cultivated" bands with pixel value 2 (i.e., cultivated areas) in our analysis since we were solely interested in identifying and mapping winter cover crop and non-cover crop areas. Finally, we clipped the CDL image collection to a study region for final analysis and used GEE's "updateMask" function to mask out any "non-cultivated" pixels from our analysis and only kept the "cultivated" area pixels.

3.2.5. Algorithms development for classifying cover and non-cover crops area

A large region makes identifying and mapping winter cover crops difficult, given the heterogenous cover crop planting and termination dates. Compounding issues include temperature and rainfall fluctuations. However, when training the model, we could map and classify winter cover and non-cover crop production areas using the appropriate classification algorithm and field-level ground-truthed data. This study used a pixel-based method to classify the winter cover crop and non-cover crop areas. After filtering government cover crop training data provided by USDA-NRCS and using the threshold method (see section 3.2.2 and Fig. 1), we split ground-truthed data into training (70%) and validation (30%) for final classification using the GEE platform. The training data is ground-truthed, meaning it has been verified by field observations, and serves as a reference dataset for classifying cover crops in the study area. Pixels representing government-subsidized (see section 3.2.2) cover crop fields were divided into training and validation datasets to mitigate spatial autocorrelation, as including pixels from a field both in the training and validation datasets can frequently result in overestimation of classification accuracy due to autocorrelation. This ensures that pixels from a field are only included in one of the two datasets, not both (Kc et al., 2021b).

The nonparametric RF classifier was used to categorize the final image composites into a binary cover and non-cover crop classification (Kc et al., 2021b; Ok et al., 2012; Pal, 2005). For applications involving crop classifications in particular, RF has been shown to frequently outperform other classification methods (Nitze et al., 2012; Ok et al., 2012). Numerous decision trees make up an RF algorithm, and the RF method trains its trees by bagging or bootstrap aggregating. An ensemble meta-algorithm, called bagging, increases the precision of machine learning algorithms. Different decision trees are trained using the training data. This dataset is made up of observations and characteristics that are chosen at random when the nodes are separated. Based on the predictions made by the decision trees, the RF algorithm determines the outcome. It makes predictions using a majority-voting system and averaging the results from different trees. For instance, a training dataset containing binary attributes is used in this study (cover crop and non-cover crop). The RF classifier divides this dataset into multiple subsets. Each decision tree in the RF network is allocated to one of these subsets. The binary output of each decision tree indicates whether the sampled pixel falls within the cover crop or non-cover crop categories. The RF classifier then compiles the majority votes from each tree to determine whether a pixel is a cover crop. To decide which features were most important in an RF model, we calculated their relative importance using an equation that divides the importance value of each feature by the total sum of all importance values for all features in the model (equation 1). This gives us the percentage (%) contribution of each feature to the overall feature importance, allowing us to identify the most important features (see section 3.2).

$$\text{Feature importance (\%)} = \frac{(Variable\ importance\ value)}{(Total\ sum\ of\ all\ importance\ variables)}\ x\ 100 \quad \ldots\ldots\ldots\ldots\ldots\ldots \quad (1)$$

A common misconception is that the accuracy of the findings increases as the number of trees grows. Oshiro et al. (2012) reported that increasing the number of trees is both ineffective and computationally costly and may not always result in the RF with more trees performing noticeably better than an earlier RF with fewer trees. Results from Oshiro et al. (2012) are supported by an example graph from our methodology (Fig. 2). Increasing the number of trees in the RF did not improve overall model accuracy in our study. The tree numbers were set to 10 in this study for all RF classifiers based on these results, and other variables were set to default based on industry standards, although there are options in GEE to modify the hyperparameters (Belgiu & Drăgu, 2016).

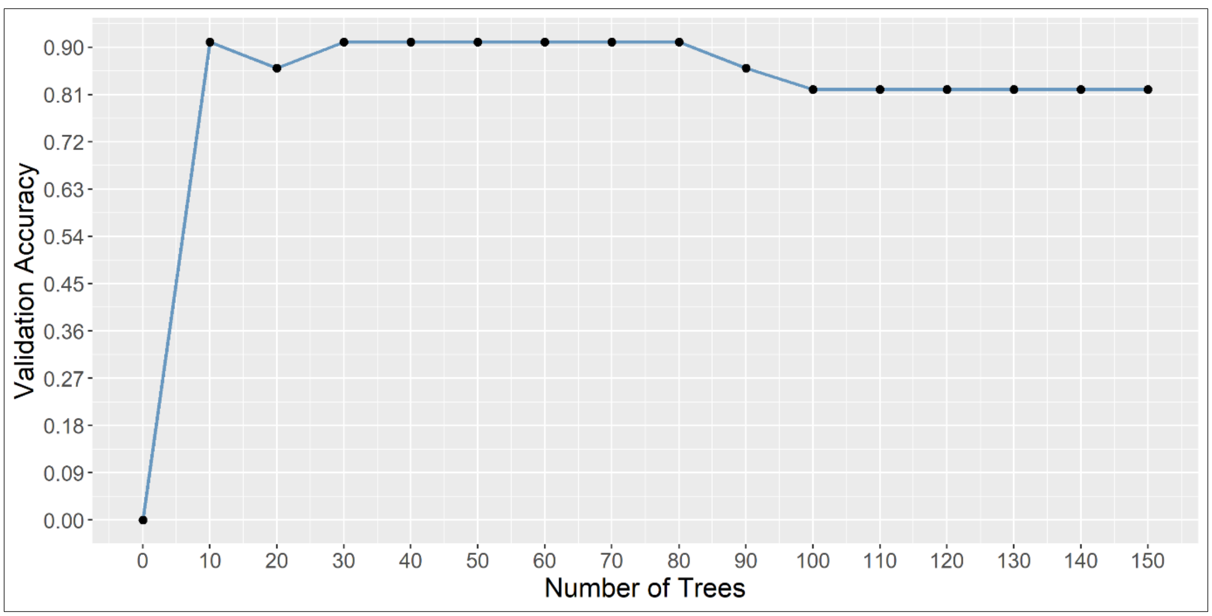

Fig. 2: Hyperparameter tuning for the number of tree parameters generated by GEE using 2013 training data.

After defining the hyperparameters and related features, the RF classifier was first trained using 70% training data so that the model could learn from it, and then with the remaining 30% test data to check the trained classifier's accuracy. The accuracy of the classification results was evaluated using an aggregate confusion matrix that combined the distribution of classification results for the test validation datasets with their corresponding actual classes across all years. This was done by summing the values for each class in the confusion matrix (see section 3.1: Table 1). Additionally, statistics including producer accuracy (PA) [(% of the ground-truthed class that was correctly identified)], user accuracy (UA) [(% of the predicted class that were correctly identified as a ground-truthed class)], kappa coefficient (k) [(measures the agreement between classification and ground-truthed values)], and overall accuracy (OA) [(metric for evaluating classification model performance)] were estimated.

3.2.6. Generate pixel-based NDVI time series, average spectral signature, and temporal phenology profile

Crop phenological or cropping cycle (i.e., greening, peak, senescence) information is essential in crop identification. Using remote sensing techniques and applying different vegetation indices and algorithms, we can discriminate between cultivated and non-cultivated areas (Kibret et al., 2020). Winter cover crops have a distinct phenology, and different types of cover crops have different types of crop phenology, and thus different spectral reflections are observed (Pan et al., 2012; Prabhakara et al., 2015b). Although we do not have specific information on the winter cover crop types from the NRCS dataset (see section 3.2.2), we know the approximate growth cycle or temporal phenology of winter cover crops in the study area to which this methodology was applied. We know when cover crops typically break their winter dormancy, and we know peak growth periods and senescence timing (see section 3.2.3). The

NRCS conservation programs require farmers to plant and terminate cover crops within a specific window. Furthermore, NRCS encourages farmers to terminate cover crops after March/April to promote nutrient uptake by the subsequent crop once the cover crop has been terminated. It is important to note that crop phenology and planting time can vary spatially and temporally, given different climatic factors like air temperature, rainfall, snow, soil properties, and other associated factors that are expected to vary throughout a region. Nonetheless, the cultivated areas in a region are relatively homogenous when winter cover crops are grown, thus we expect relatively little variation in spectral response.

One of the goals of this research is to examine the changes in cover crop vigor and growth over time in a large agricultural region by analyzing the mean NDVI values. Boumis & Peter (2021) created a time-series matrix visualization tool to show multiscale temporal patterns and the productivity of rice farming in Vietnam as measured via enhanced vegetation index using the NASA Moderate Resolution Imaging Spectroradiometer (MODIS) data product. We have adopted the same methodology but with different data products and indices to generate pixel-based time series for cover crops in the application region. To generate pixel-based NDVI time series for cover crop growing areas, we used the Landsat 8-day NDVI composite. The composites were generated using all the scenes from each 8-day period between 2013 and 2019. We first filtered this image composite by month and year according to our predetermined temporal month range. Secondly, we calculated the mean cover crop NDVI by year for time-series analysis. An R script was utilized to generate a linear regression slope plot for all possible year combinations within a given temporal range, which included examining data from 2013-2014, 2013-2015, 2013-2016, and so on up to 2019. The input data required a two-column CSV format of years and NDVI values. The time-series vector regression parameters were extracted using linear regression modeling to estimate trends (equation 2) (Jong et al., 2011, Fensholt & Proud, 2012). The results include a time-series matrix that shows the slope direction based on linear regression and the slope value plotted with colors indicating their magnitude (see section 3.4) (Boumis & Peter, 2021).

$$y_i = \beta_0 + \beta_1 * x + \varepsilon_i \quad \ldots\ldots (2)$$

where, y_i represents the study area mean yearly NDVI value for cover crop, x represents the year, ranging from 2013 to 2019 (i.e., x = 2013, 2014, ..., 2019), β_0 represents the y-intercept of the regression line, β_1 represents the slope of the regression line, and ε_i is the error term.

The linear regression slope direction and magnitude plot will show whether there is a positive or negative trend in mean cover crop NDVI values over time and how strong or weak that trend is and can help to identify years when cover crops are thriving or struggling. It is essential to consider the limitations of the analysis while interpreting the results. The linear trend analysis assumes a linear relationship between the years and NDVI values, which might not always be a valid assumption.

Identifying and mapping winter cover crop growing locations using remote sensing methods requires knowledge about different vegetation indices (VI) and their spectral reflectance. Vegetation, soil, water, cloud cover, and topography interact with solar radiation differently and produce different spectral reflectance patterns. In this study, we applied a commonly used VI, the Normalized Difference Vegetation Index (NDVI) (Camps-Valls et al., 2021b). We randomly selected training points per group per year to capture the average spectral signature and NDVI temporal profile for cover and non-cover crop pixels. A linear interpolation technique was used to fill any gaps due to cloud masking (Lepot et al., 2017). For this part of the analysis, the selected months for NDVI value measurements were from September through May, which allowed us to observe the changes in winter crop phenology. These months were chosen purposely based on the growing cycle of cover crops in the application region, where planting typically occurs in September-October and termination in April-May. Following Jong et al. (2011), a conceptual diagram of pixel-based mean time series of winter cover crop temporal phenology with respect to NDVI value is shown in (Fig. 3).

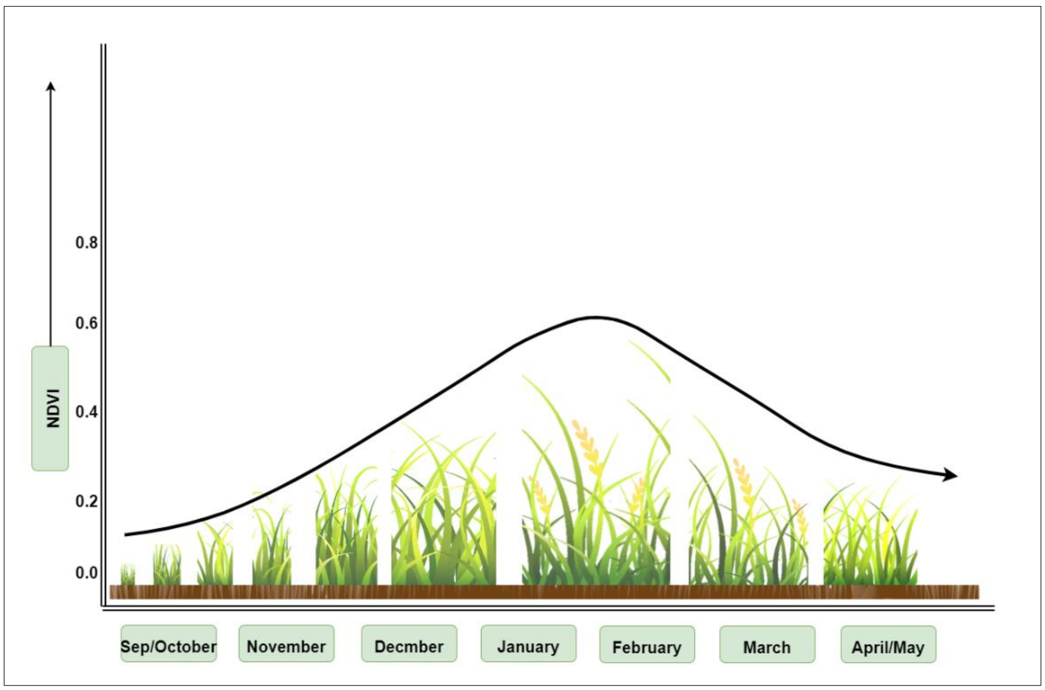

Fig. 3: Conceptual average phenology of winter cover crops in the application area, modified from Jong et al. (2011). Note: To prevent misclassification, winter satellite images were collected for five months (November to March) to identify the winter cover crop each year from 2013 to 2019. The first two months September/October, and last two months, April/May, were used only for estimating the NDVI temporal profile analysis (start and end of the cover crop growing season).

3.2.7. Study area

The Mississippi Alluvial Plain's economy, which includes much of eastern Arkansas, western Mississippi, and northeastern Louisiana, primarily depends on commercial agriculture

(Alhassan et al., 2019). The area of study for the application of the methodology developed is the Arkansas portion of the MAP, consisting of all or parts of 27 counties (Fig. 4). The MAP study area's aggregate agriculture sector contributes $31 billion annually to Arkansas's economy (English & Popp, 2022). The monthly mean precipitation and temperature patterns for the study area from 2013 to 2020 are summarized in the appendix (Fig. A1). A humid subtropical climate characterizes the MAP region, which normally experiences hot and humid summers, mild winters, and abundant rainfall throughout the year. The region is prone to frequent thunderstorms, occasional tornadoes, and flooding due to its location along the Mississippi River. The climatic conditions in the area are suitable for cultivating a variety of crops, including cotton (*Gossypium herbaceum* L.), soybeans [*Glycine max* (L.) Merr.], rice *(Oryza sativa* L.), and corn (*Zea mays* L.). Winter cover crops have the most substantial ground coverage in January, February, and March in Arkansas (USDA, 2015). Understanding the monthly temporal range when temperatures decrease in the fall (post-primary crop harvest) and increase again in the spring (pre-primary crop planting) and how this pattern affects winter cover crop growth can provide valuable insights for farmers and policymakers. Such insights can inform decision-making regarding crop management practices, water management, and disaster preparedness.

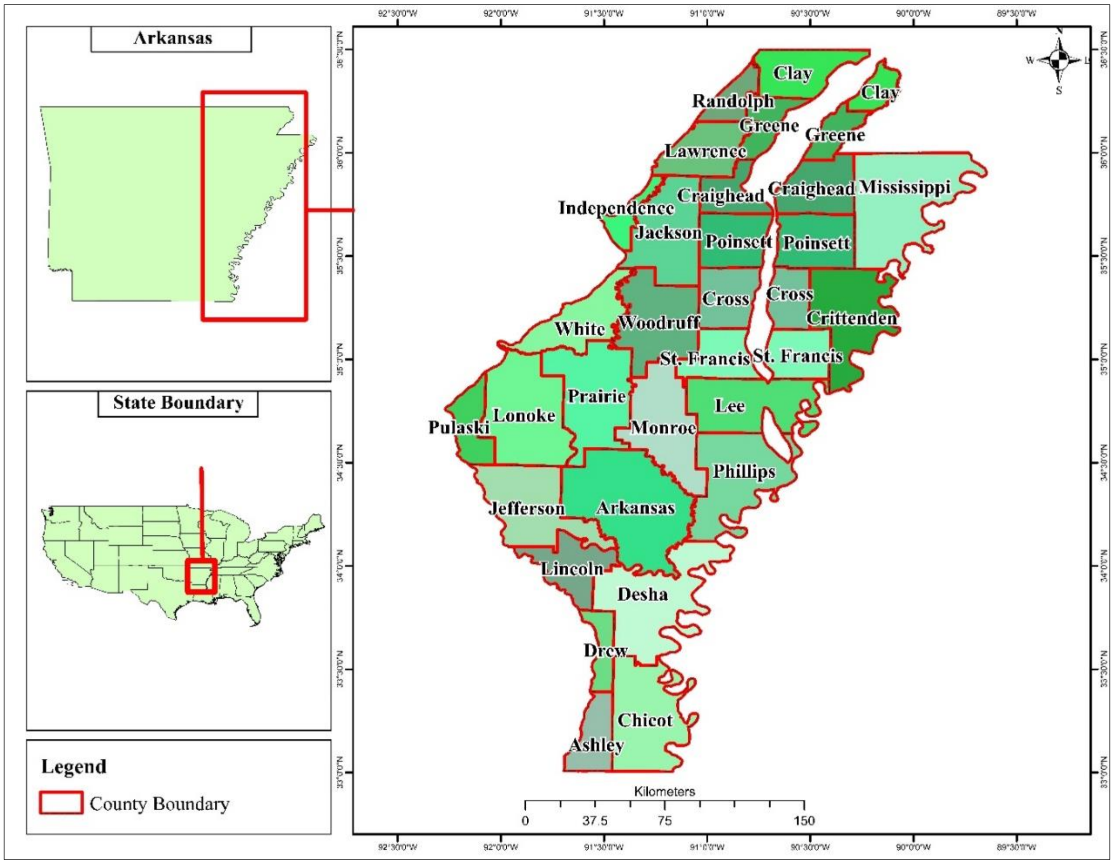

Fig. 4: The Arkansas portion of the Mississippi Alluvial Plain study area

3.3 Results

3.3.1. Model evaluation and performance assessment

An aggregate confusion matrix was used to evaluate the performance of the RF classifier in distinguishing winter cover crop and non-cover crop area pixels in the MAP model-application area. The matrix, shown in Table 1, provides metrics such as PA and UA, which respectively measure how well the model identifies all samples in a particular class and the number of samples classified as a particular class that belongs to a different class. Overall accuracy (OA) is the percentage of all samples correctly classified by the model, and the Kappa coefficient (k) measures the agreement between the model and the ground-truth labels. The model achieved an OA of 97.7% and k of 0.94, indicating good performance. The PA was large for both classes (98.8% for non-cover crops and 94.3% for cover crops), while the UA was lower for the cover crop (96.4%), suggesting that some sample pixels predicted as a cover crop were non-cover crops.

Table 1: Accuracy assessment of classification results

	Class types determined from classified map				
Class types determined from reference data	Class	Cover Crop	Non-Cover Crop	Totals	Producer Accuracy (%)
	Cover Crop	267	16	283	94.3
	Non-Cover Crop	10	829	839	98.8
	Totals	277	845	1122	
	User Accuracy (%)	96.4	98.1		
	P_0/Overall Accuracy (%)				0.97
	P_e/ Probability of Agreement				0.63
	k				0.94

Note: The actual number of pixels is shown in the rows, while the predicted number is shown in the columns. The diagonal cells represent correctly classified pixels. This accuracy estimate is displayed for 30% of the samples used for validation. Each pixel represents an area of 900 m^2. Kappa (k) = P_0 - P_e / 1 - P_e. Here P_0 is the probability of agreement, and P_e is the probability of random agreement.

3.3.2. Relative feature importance of random forest model feature variables

The feature importance analysis using the RF algorithm for identifying cover crop and non-cover crop areas data revealed that the spectral indices are more important than the spectral bands for cover and non-cover crop identification (Fig. 5). In general, the spectral indices had a greater percentage of relative importance (ranging from 0.2 to 22.4%) than the spectral bands (ranging from 0 to 18.3%) across all years. Among the spectral indices, the Normalized Difference Built-up Index (NDBI), Bare Soil Index (BSI), NDVI, and Soil Adjusted Vegetation Index (SAVI) had consistently greater relative importance values over the years, suggesting their stronger predictive power for cover crop and non-cover crop classification. In contrast, the spectral bands with greater importance values were Shortwave Infrared 2 (SWIR2), Near-Infrared (NIR), and Red. A complete list of spectral bands and indices utilized for RF model learning is presented in Appendix Table A1.

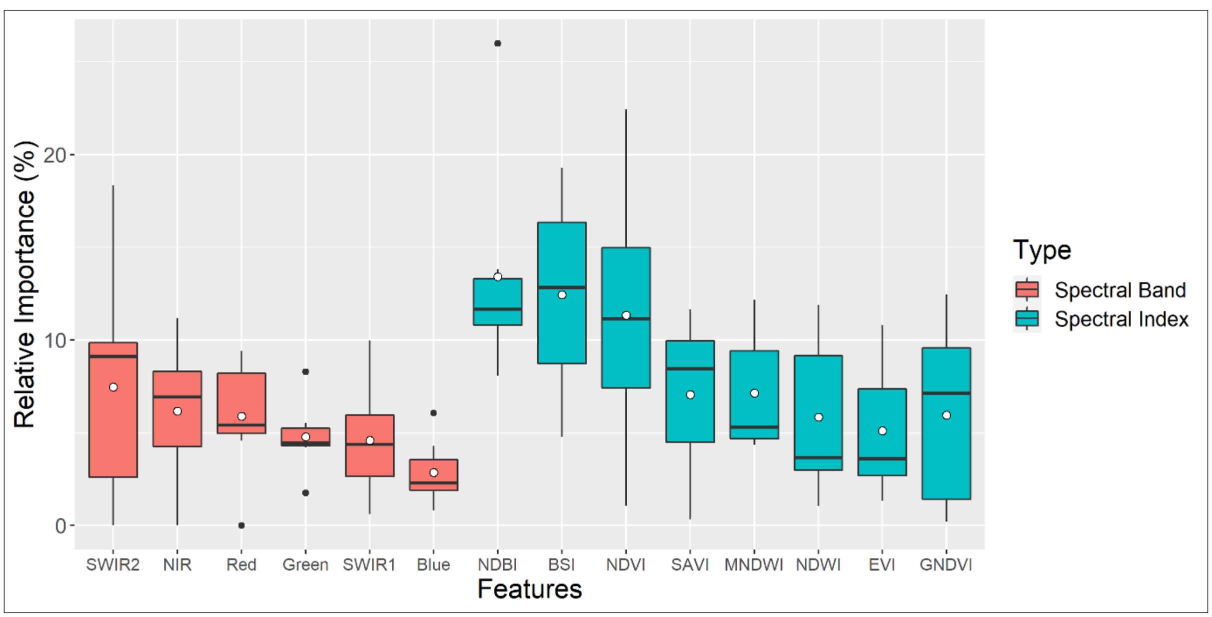

Fig. 5: Relative importance of model variables grouped by spectral bands and spectral indices. [Note: The feature importance percentage, obtained from the Random Forest algorithm's supervised classification of cover crop and non-cover crop pixels (see equation 1), indicates the greater predictive power of spectral bands and indices with a higher relative importance percentage. A white circle denotes the mean value, and black dots represent outliers.]

3.3.3. Trends of model predicted county-wise cover crop adoption

The adoption of cover crops in the MAP research region between 2013 and 2019 was predicted using vetted RF classification. A summary of the cover crop adoption percentage of total planted acres by county and year and an analysis of trends in cover crop adoption (acreage) over time is shown in (Fig. 6). Percentages were calculated annually since the cultivated land area varied over time. Winter cover crops were planted on 677,272 acres (274,082.25 ha) in 2013 (10.8% of the total 2013 cropland). The adoption decreased in the year 2014 to 440,666 acres (178,331.20 ha) (7.1% of the total 2014 cropland), increased to 615,086 acres (248,916.47 ha) (9.8% of the total 2015 cropland) in 2015, and again decreased to 561,533 (227,244.34 ha) (9% of the total 2016 cropland) in 2016, and to 406,832 acres (164,639.07 ha) (6.5% of the total 2017 cropland) in 2017. In 2017, the lowest predicted amount of cover crops were planted. The adoption of winter cover crops increased over the last two years in the data set, with 880,185 acres (356,198.23 ha) (13.9% of the total 2018 cropland) and 904,624 acres (366,088.34 ha) (14.3% of the total 2019 cropland) in 2018 and 2019, respectively. With some year-to-year changes, there was a 34% increase in cover crop adoption in the study area between 2013 and 2019. Similar county details on cover crop acreage over time are shown in the appendix (Fig. A2).

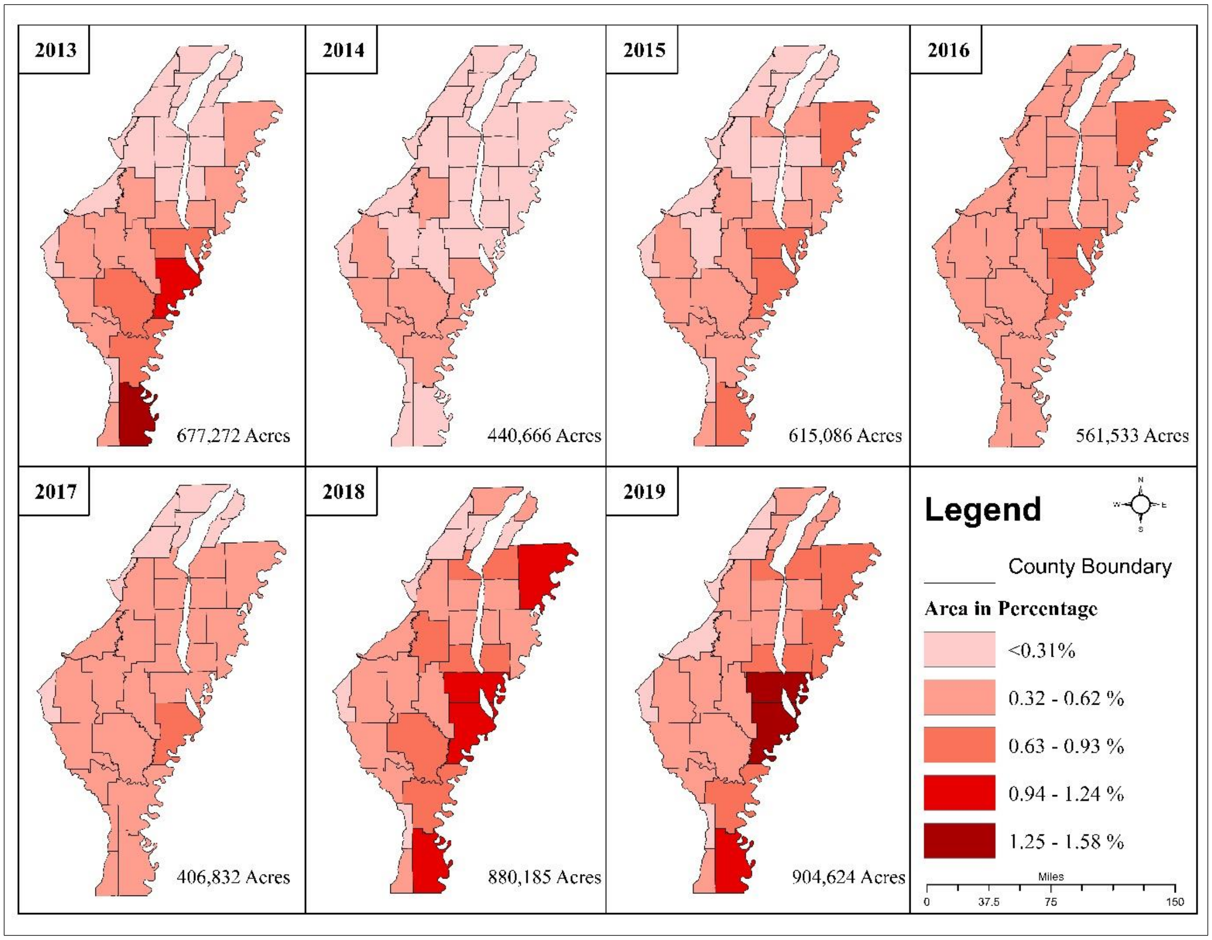

Fig. 6: Model predicted total cover crop adoption percentage range by county. Note: The map included in the figure displays two things: (1) the total cover crop adoption percentage by county and year, (2) the acreage value shown in the lower right corner of each year's map, providing insights into the trends in cover crop adoption from 2013 to 2019. The cover crop adoption percentages were calculated annually, accounting for variations in the cultivated cropland area.

3.3.4. NDVI linear trend time series analysis for cover crop areas

The analysis of the NDVI time-series trends for cover crop areas in the MAP region from 2013 to 2019 revealed both positive and negative trends. Fig. 7 displays the direction and magnitude of the regression slopes for the average NDVI values, providing insights into the growth and development of cover crops over time. In the early years (2013-2015), a general decline in NDVI values is observed, indicating a potential decrease in vegetation health. This could be attributed to various factors, including weather conditions or economic constraints.

However, the later years (2016-2019) show a mix of positive and negative trends, suggesting a more variable vegetation health dynamic during this period.

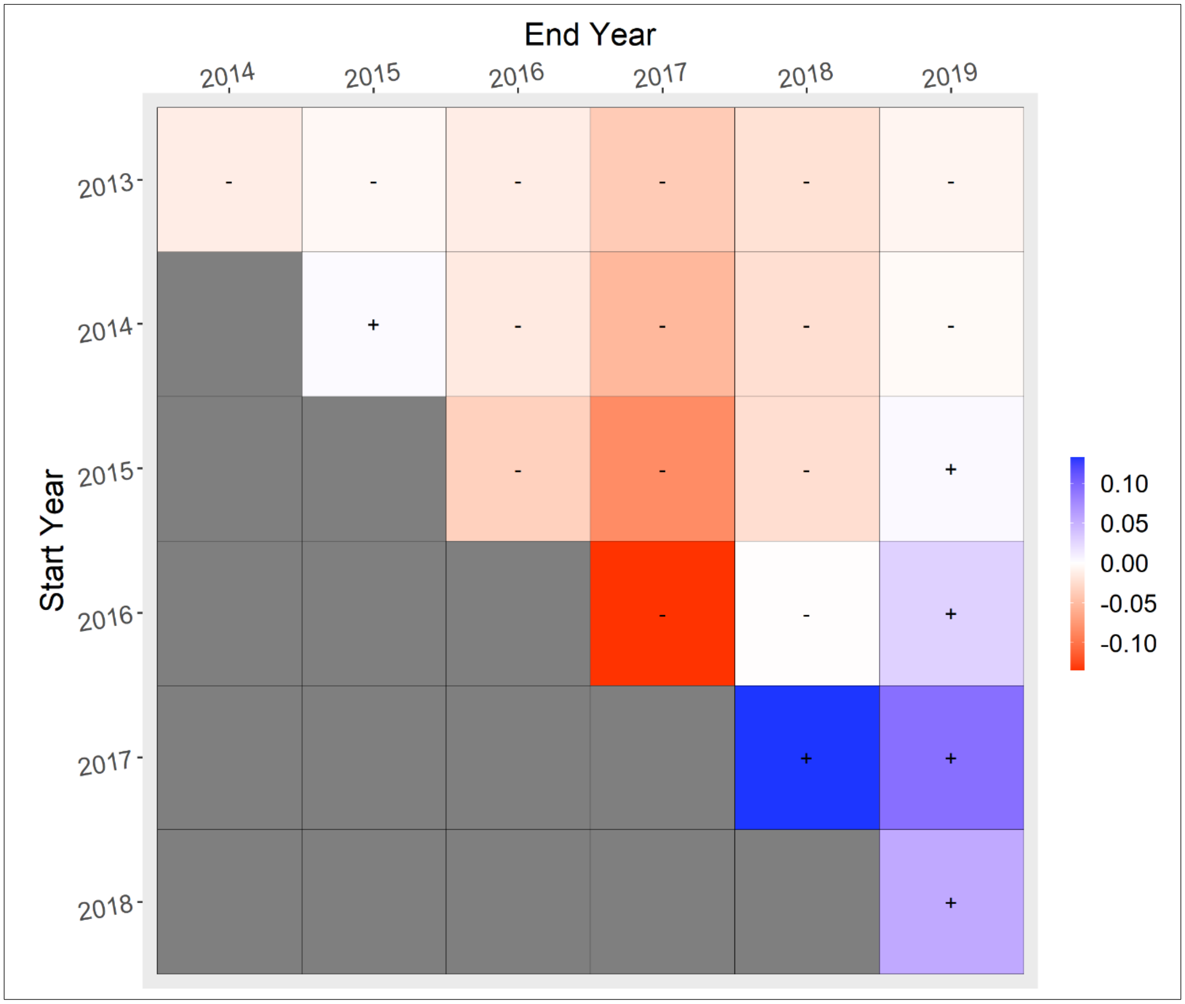

Fig. 7: Mean NDVI time series slope direction and magnitude for all study cover crop areas. Note: Mean NDVI time series slope magnitude (-0.10 to 0.10) and direction (- or +) for all study cover crop areas from 2013 to 2019.

3.3.5. Spectral reflectance properties of winter cover crop and non-cover crop pixels

Spectral reflectance or signature is a key concept in remote sensing and is mainly used in various crop identification using optical satellite imagery. The six spectral bands of blue, green, red, NIR, SWIR-1, and SWIR-2 were used to categorize spectral reflectance. Because of the variations in spectral bands and associated range of wavelengths, cover crop pixels are easily differentiated from non-cover crop pixels. The mean spectral reflectance pattern for cover crop and non-cover crop pixels per year, along with the NDVI value as a comparison, is shown in (Fig. 8). Reflectance values for cover crop areas are low in blue (0.45 - 0.51 µm), green (0.53 - 0.59 µm), and red (0.64 - 0.67 µm) wavelengths, but tend to rise in NIR (0.85 - 0.88 µm) wavelengths (Fig. 8-a). A separate NDVI index has been added to this set of bands to observe the change in reflectance value that occurs when several bands are combined to create a vegetation index that may be used to detect and distinguish vegetation pixels from other land use pixels. It should be noted that the NDVI, which is the ratio between the reflectance measured in the NIR and Red bands, has a maximum reflectance value between 0.35 and 0.45 and can easily identify cover crop pixels.

Similar types of analysis, as displayed in (Fig. 8-b), were observed for the spectral pattern of areas without cover crops, i.e., bare soil. The spectral reflectance of bare soil exhibits similar responses as cover crops in the blue, green, and red bands. However, the reflectance values for bare soil are lower in the NIR and NDVI. In contrast, the spectral responses of bare soil are greater than cover crops in the SWIR-1 and SWIR-2 bands. The low NDVI values indicate the presence of bare soil areas and dry crop residues or grey grassland. Soil covered with crop residue can have spectral responses similar to cover crops, depending on the amount and type of residue. This can make distinguishing these areas from actual cover crops challenging, especially if the residue is still green and actively photosynthesizing. Fig. 8-c represents the mean spectral reflectance of cover and non-cover crop (i.e., bare soil) pixels. The greatest average value differences are apparent for NIR and NDVI values, making those values good predictors, corroborating findings (Fig. 5).

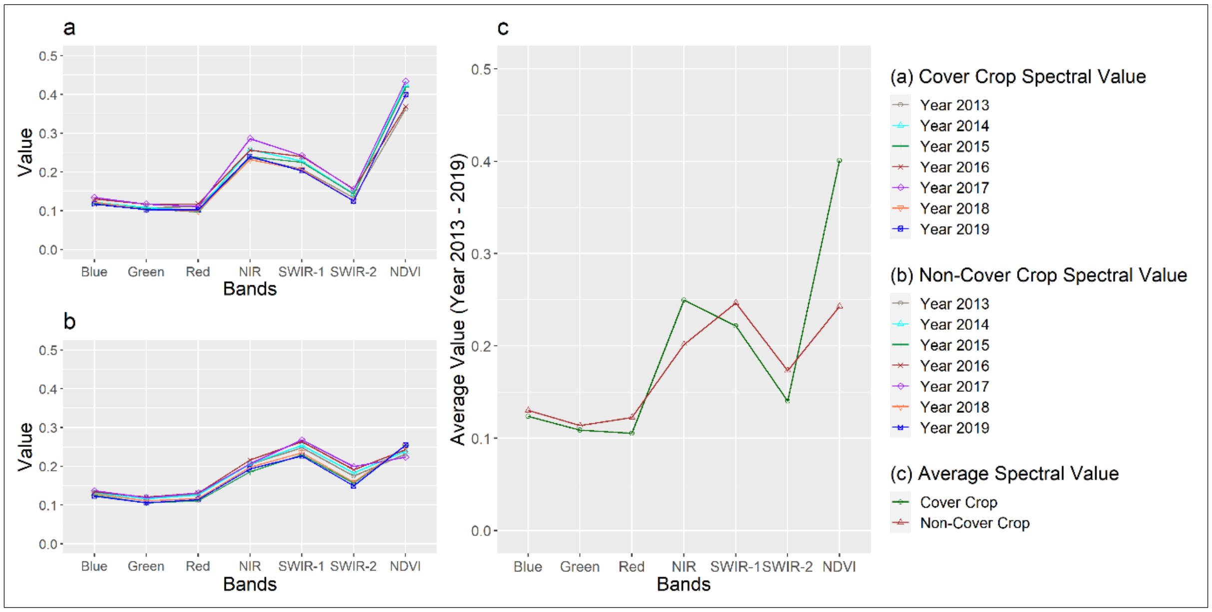

Fig. 8: Average spectral reflectance value per band and NDVI from randomly selected training points by year for cover and non-cover crop (i.e., bare soil) areas. Panel (a) shows the mean spectral values of cover crop areas for each year's randomly selected training points. Panel (b) shows the mean spectral values of non-cover crop areas for each year's randomly selected training points. Panel (c) displays the mean spectral values from 2013 to 2019 for both winter cover crop and non-cover crop areas. As a point of reference, the NDVI value is displayed here. The difference between NIR (which vegetation strongly reflects) and Red (which vegetation absorbs) bands are represented by the NDVI, which is an index rather than a band.

3.3.6. NDVI temporal profile of winter cover and non-cover crops pixels

The monthly NDVI temporal fluctuations from 2013 to 2019 for cover and non-cover crop areas (i.e., bare soil) are shown in (Fig. 9). With minor monthly variations, the yearly variance showed remarkably similar patterns for cover crop and non-cover types. The monthly NDVI temporal profile of the winter cover crops for each year is shown in (Fig. 9-a). These temporal profiles provide a thorough analysis of the state and health of the cover crop across the years and estimate the start and end of the cover crop growing season. Additionally, these temporal profiles demonstrate the accuracy of the model training data in identifying cover crop areas. Fig. 9-b also displays the NDVI temporal profile for regions without cover crops. The NDVI values of areas without cover crops at the beginning of winter are relatively large, gradually decreasing and increasing again through the end of the winter season. The NDVI values of areas without cover crops at the beginning of winter are relatively large due to the presence of bare soil and low vegetation, gradually decreasing during the winter months and increasing again through the end of the winter season as new vegetation emerges. The average NDVI temporal profile from 2013 to 2019 is shown in (Fig. 9-c). Pattern differences between cover and non-cover crops emerge clearly across the seven-year average.

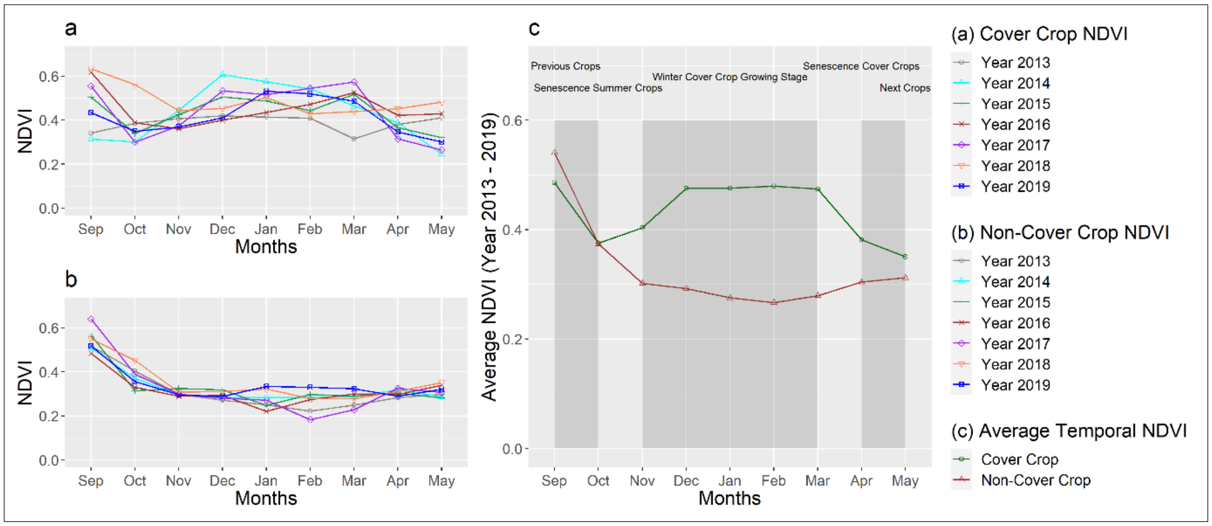

Fig. 9: Average NDVI temporal profile from cover and non-cover crop (i.e., bare soil) training points by years and months. Panel (a) displays each year's monthly mean NDVI temporal profile of the winter cover crop areas. Panel (b) displays each year's monthly mean NDVI temporal profile of the winter non-cover crop areas. Panel (c) displays the mean NDVI temporal profile from 2013 to 2019 for both winter cover crop and non-cover crop areas.

3.4 Discussion

3.4.1. Accuracy of the binary class model and the significance of the model feature variables

This study used the MAP area of Arkansas to identify and map winter cover crop adoption using a newly developed, remote-sensing methodology. The MAP study region is a unique region for cover-crop mapping as the region suffers from conservation issues, such as soil degradation and water pollution, due to the long history of intensive row-crop cultivation (Kladivko et al., 2014; Knight et al., 2013; Yasarer et al., 2020). This study identified and classified winter cover and non-cover crop areas using remotely sensed satellite data combined with USDA-NRCS novel multi-year ground-truthed training data. Our model was robustly accurate in identifying cover crops and non-cover crop areas, with cover crop class producer and user accuracies ranging between 94.3 and 96.4%. These values are greater than those of other land cover products currently available, such as the CDL, which typically exhibits total crop mapping accuracies ranging from 85 to 95% for major crop categories (Boryan et al., 2011; Lin et al., 2022; Reitsma et al., 2016).

We compared our results with other cover crop type mapping studies and showed that our yearly cover crop map products exhibited greater accuracy. However, it is challenging to directly compare accuracy statistics with results from previous research because of variations in class types, areas of study, and validation techniques. When predicting cover crops for Knox County, Indiana, Tao & You (2019) used a multi-layer perceptron neural network and achieved an accuracy of 93% and kappa of 0.76. Using four cover crop categories, Kc et al. (2021) created a spatial and temporal inventory of seasonal winter cover cropping practices in the Ohio Maumee River watershed from 2008 to 2019 and reported an overall classification accuracy of 75%, with a kappa coefficient of 0.63 using an RF classifier. Seifert et al. (2018) developed a RF classifier with an overall 91.5% accuracy and a 0.68 kappa statistic to study cover cropping practices and their impact on crop productivity in eight midwestern US states. According to the findings, we argue that our yearly cover-crop map products achieved greater accuracy than previous cover-crop-type-mapping methods (Barnes et al., 2021b; Kc et al., 2021b; Seifert et al., 2018; Y. Tao & You, 2019).

Overall, we found that the NDBI, BSI, NDVI, and a few additional bands and indices were enough to identify and distinguish between cover crops and non-cover crop areas in the MAP study region. The NDBI and BSI indices are significant in our research area since there are more non-cover crop areas than cover crop areas. In our research area, if there were built-up areas in addition to bare land with similar spectral signatures, we used both the BSI and NDBI indices to enable our model to learn from spectral reflectance. Except for the thermal band, the other parts of the electromagnetic spectrum were investigated, which are connected to various aspects of vegetation, and each offers specific information for detection. These results confirmed the importance of utilizing Landsat 8 bands and band ratio index data to classify and map cover and non-cover crops in the model application area. Our research confirms findings from other studies that it is crucial to use several indices and bands other than a single index, such as NDVI, to enhance the detection of winter cover crops (Barnes et al., 2021b; Seifert et al., 2018). External factors, such as weather patterns and land management practices, should also be considered, as they can influence the performance of spectral bands and indices. Our results highlight the importance of selecting the appropriate spectral bands and indices for cover and non-cover crop identification and the potential of machine-learning algorithms, such as RF, for extracting meaningful information from complex remote sensing datasets.

An essential element for large-area cover-crop mapping is the availability of trustworthy and reliable ground-truthed data. A vast array of ground-truthed data are needed to make long-standing products like USDA's CDL. Aside from a few winter crops, researchers cannot use specific cover crop information or train models using CDL data, which are created by merging images from several optical sensors and field data (Lark et al., 2021). The yearly CDL offers excellent ground-truthed data for mapping different crop types in the continental US. Still, they are typically unavailable as daily or monthly data, which is a crucial requirement for mapping winter cover crops since most of the growing season for these cover crops overlaps between two calendar years. However, CDL has a cultivated data layer that may be utilized to prevent mixed pixel issues and, when applied in accordance with our proposed methodology, can increase model accuracy in a binary classification problem.

3.4.2. Assessment of the linear trends in the cover crop NDVI, the spectral signature, and the greening and browning trends

The phenology of various types of crops has historically been studied via field surveys carried out during the growing season. In contrast, visual assessments of spatial and temporal changes in crop phenology are arbitrary, labor-intensive, and infeasible across a large geographic region (Piao et al., 2019). Due to recent developments in remote sensing systems and sensors, many researchers now use publicly available data with better spatial, spectral, temporal, and radiometric precision to study a crop's phenological development through time and space. In this study, we investigated the phenology of winter cover crops using annual time series, monthly time series, and mean temporal profile from 2013 to 2019. For the study area, positive trends are linked to a yearly increase in mean NDVI value, whereas negative trends are connected to a decrease in mean NDVI value annually. Policymakers may use these results to understand better the reasons behind the yearly variance in the mean cover crop NDVI. This information and other related data can be used to describe changes in the market and weather conditions that could have affected cover crop adoption acres in a particular year or across years.

Additionally, our study assessed the effectiveness of employing spectral bands to identify areas with and without cover crops. Changes in spectral bands and the accompanying range of wavelengths allowed cover crop pixels to be distinguished from non-cover crop pixels. A similar pattern can be seen over the years with only minor variations. This slight annual variation is caused by the fact that various types of cover crops exhibit slightly different types of reflectance value. The vegetation index and photosynthetic activity are proxied by the red, green, and blue and NIR wavelengths (Carlson & Riziley, 1997). Non-photosynthetically active vegetation may be distinguished from bare soils using wavelengths in the SWIR that target the vegetation's water, cellulose, and lignin (Asner & Lobell, 2000; Peña-Barragán et al., 2011). Overall, we showed that spectral bands and other spectral indices were sufficient to identify cover and non-cover crop areas in the MAP study region over the winter time. Our research confirms findings from other studies that utilizing more than just vegetation indices is necessary to enhance the detection of cover crops (Barnes et al., 2021b; Seifert et al., 2018; Sonmez & Slater, 2016b).

Currently, there are no specific planting or termination dates for winter cover crops within the MAP study region. Using a time-series approach for a large geographic area, like MAP, we suggest a new methodology in this study to monitor the mean NDVI value of the cover crop at first by monthly intervals and later to show changes by yearly intervals. When tracking and evaluating the growth condition of cover crops, the monthly temporal NDVI profile can be useful. Due to variations in the timing of green-up, peak greenness, and senescence/termination, each year’s cover crop type exhibited different patterns. Additionally, specific years have low

NDVI levels, while others exhibit large values. One of the explanations is that, in Arkansas, winter cover crops are sown at somewhat different intervals of time and that the length of time changes from year to year and from north to south. Another important finding is that the NDVI values of areas without cover crops at the beginning of winter are large because some cash crops are still growing late into the fall. Apart from a few exceptions, most of the winter cover crops are sown between September and October (Roberts et al., 2018). This explains why the NDVI values in October decreased sharply, as it was the time when neither the main crop nor the cover crop was actively growing. Between October and November, the NDVI values increase as the winter cover crop develops. Cover crops continue growing, which increases the NDVI values. The NDVI values decrease as cover crops get mature and fade in color as they continue to decline through the end of the winter season or are terminated. Finally, the mean NDVI value for months and years was constructed by the average cover crop and non-cover crop NDVI temporal profile from 2013 to 2019. Researchers, producers, and policymakers can use this information to predict the cover crop growing timeframe using plus or minus one or two months as a buffer interval. Monitoring cover crops, which are planted over a short period often masked by cloud cover with limited quality satellite images, may be challenging with these techniques. Although researchers have used a variety of time-series gap-filling methods, each of these approaches has drawbacks and limitations, so care must be taken when using them (Chen et al., 2004; Chen et al., 2021; Martínez & Gilabert, 2009; Sakamoto et al., 2005).

Our results suggest that the adoption of cover crops increased after 2018, which external factors, such as policy changes might influence. The Farm Bill of 2014 and the subsequent Farm Bill of 2018 (USDA ERS, 2014, 2018) could have contributed to the increased adoption of cover crops by providing financial incentives and technical support for farmers to implement conservation practices. In contrast, the decrease in mean cover crop NDVI values in 2017 could be attributed to various factors, such as weather conditions, economic constraints, or regional challenges. Hurricane Harvey in 2017 (Blake and Zelinsky, 2018; Hightower, 2017) a late-season storm that caused significant wind, rain, and flood damage in the MAP region, potentially affecting crop growth and the ability of farmers to plant cover crops during the 2017 winter. In conclusion, the observed trends in NDVI values for cover crop areas in the MAP region can be attributed to a combination of policy changes, such as the Farm Bills of 2014 and 2018, and various environmental factors, such as weather conditions and regional challenges like Hurricane Harvey in 2017.

The methodology proposed in this study could be extended and reproduced in other agricultural regions if good-quality training data are available. By integrating sensor sources and ground-truthed data, we showed that it is possible to obtain cover crop and non-cover crop classifications with roughly similar detail in class labels for larger areas, multiple years, and homogeneous landscapes, like the MAP study area. This approach can be used in other regions to accurately identify and map cover crop adoption by modifying certain code and variables.

3.4.3. Study limitations and future work

This study fills in data gaps by identifying winter cover crop areas for seven years in the MAP region, but it has some drawbacks that could be addressed with future research. The USDA-NRCS database was used to generate multi-year training datasets, filtered, and prepared following the procedure detailed in the methodology sections. The types of cover crops, however, were not specified in that database, which restricts the scope of our study to only one combined cover crop class. Thus, if weeds and cover crops have spectrally similar patterns, our RF model may treat those pixels equally, meaning some weed pixels could be considered cover crops. Clearing very tiny and isolated pixels, we attempted to minimize this problem. We also adopted an NDVI threshold value to address this problem, as weeds are often sparsely dispersed in cropland and have a low NDVI value. Some of these results need to be interpreted with caution. Governmental data suggested that cover crops were present in certain locations, while satellite images revealed a lack of vegetation and vice versa. We applied the NDVI threshold rule to classify areas with active vegetation as cover crop areas and non-vegetative areas as non-cover crop areas. Another limitation is that certain cover crop locations with poor GPS accuracy were excluded from this research. Besides, many regions would not qualify as cover crop areas due to using the NDVI threshold of less than 0.3. This study used a pixel-based classification approach to distinguish between areas with and without cover crops throughout the winter months.

The significant local spatial variability between surrounding pixels, which results in the speckled or salt-and-pepper effect, is one of the main drawbacks of pixel-based classification. However, this issue may be solved by adopting modern techniques like object-based classification (OBIA). The OBIA approach divides an image into objects or segments based on spatially connected pixels with similar spectral properties instead of classifying each pixel solely based on its spectral content. These objects are then classified based on their spectral, spatial, and contextual attributes and their interrelations across scales. The method may result in improvements in classification accuracy. Another limitation of our method is its inability to distinguish between multiple growing-season anomalies resulting from winter frost temporarily killing cover crops. Given the size of the MAP, it was challenging to obtain a collection of satellite imageries with reduced cloud cover that covered the same geographic area for several days or months during the cover crop growing season. Given that Landsat has a 16-day return period, it would be challenging to accurately identify cover crop areas and phenology if any images happened to be compromised due to cloud-masking. By using the single median image composite and linear interpolation techniques, we attempted to address this issue, although the results occasionally may portray inaccurate seasonal patterns, such as peak or senescence. To improve classification accuracy and detect multiple growing-season anomalies, future research could address the issue by integrating radar data, such as Sentinel 1, with high spatial and temporal optical data, such as PlanetScope and Sentinel 2, and most importantly, use seasonal image composites, which are often susceptible to cloud coverage.

3.5 Conclusion

Accurate mapping of cover and non-cover crop areas is a crucial prerequisite to inform agricultural decision-makers and cost-share providers that aim to develop policies that can benefit producers while maintaining or adding to environmental resources and services. With the introduction of the big-data era, the remote sensing industry's focus has shifted to combining data from several sources and scales with precise algorithms. Among many other platforms, Google Earth Engine (GEE) offers free, processed, and available satellite images and strong computing power, which may successfully address the challenging issue of massive data processing for remote sensing. Based on GEE, this study created, for the first time, a 30-m spatial and seven-year (2013 to 2019) temporal resolution binary annual datasets and then aggregated them by county in the MAP study region using Landsat 8 imageries and USDA-NRCS novel cover crop data. Additionally, the spectral signature, the greening and browning of cover crop patterns, and the linear changes in the cover crop NDVI were all explored and evaluated in this study. Results showed that, although there were slight variations among years, there was a highly correlated pattern between the winter cover crop profiles for all spectral bands. The annual variation also revealed similar cover crop and non-cover crop area patterns, with slight monthly NDVI temporal fluctuations, which can aid researchers, decision-makers, and cost-share providers by approximating the beginning and end of the crop growing season. Our ability to anticipate and quantify the impact of summer crop production gains owing to cover crop adoption for extended periods, as well as evaluate the adoption of cover crop on local soil ecosystem, biogeochemical cycles, and services, may be improved by this multi-year novel dataset. Farmers, decision-makers, and cost-share providers may use this information to develop agricultural conservation methods and land-use regulations that minimize soil erosion and climate change in the long run.

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Appendix

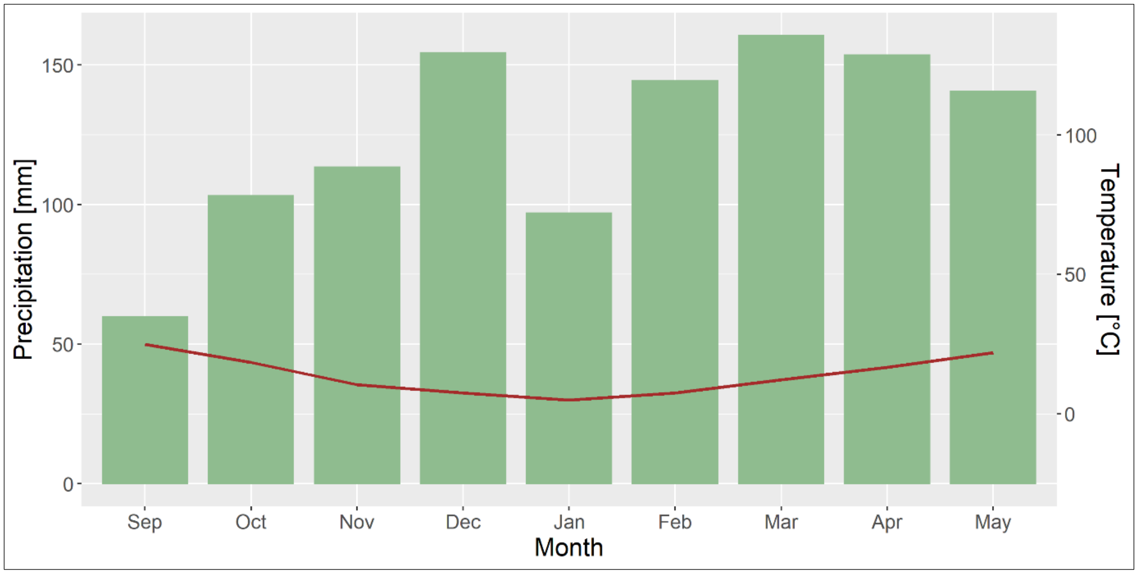

Fig. A1: Average precipitation and air temperature pattern for the study area from the year 2013 to 2020.

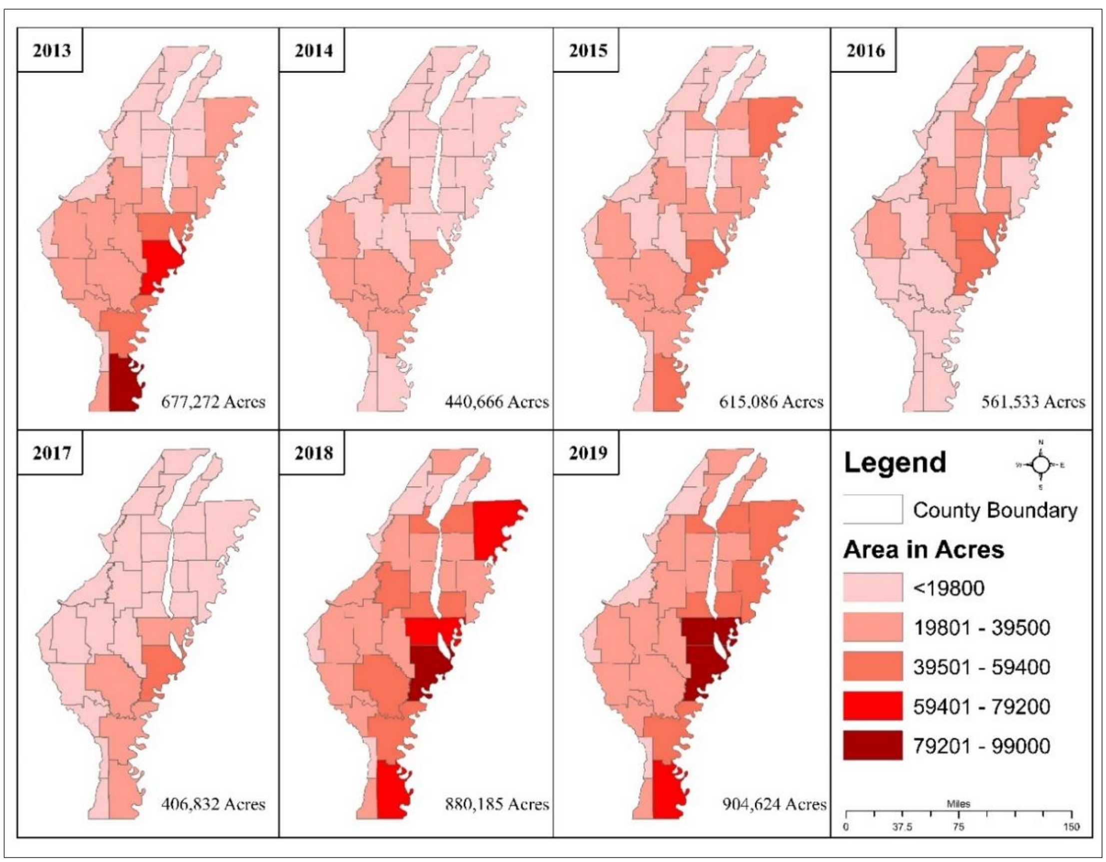

Fig. A2: Model-predicted total cover crop adoption acres by county in the Missippi Alluvial Plain.

Table A1: Description of the selected bands and indices used in the classification model.

Bands/indices	Description	Wavelength/ formula	Reference
B2	Blue	0.45 - 0.51 µm	Vermote et al. (2016)
B3	Green	0.53 - 0.59 µm	
B4	Red	0.64 - 0.67 µm	
B5	Near infrared (NIR)	0.85 - 0.88 µm	
B6	Shortwave infrared 1 (SWIR-1)	1.57 - 1.65 µm	
B7	Shortwave infrared 2 (SWIR-2)	1.57 - 1.65 µm	
NDVI	Normalized Difference Vegetation Index	(NIR – Red) / (NIR + Red)	Rouse et al. (1974)
GNDVI	Green Normalized Difference Vegetation Index	(NIR – Green) / (NIR + Green)	Gitelson & Merzlyak (1998)
NDBI	Normalized Difference Built-Up Index	(SWIR-1 – NIR) / (SWIR-1 + NIR)	Zha et al. (2003)
MNDWI	Modified Normalized Difference Water Index	(Green – SWIR-1) / (Green + SWIR-1)	Xu (2006)
BSI	Bare Soil Index	((SWIR-1 + Red) – (NIR + Blue)) / ((SWIR-1 + Red) + (NIR + Blue))	Chen et al. (2004)
SAVI	Soil Adjusted Vegetation Index	(1 + 0.5) * (NIR – RED) / (NIR + RED + 0.5)	Huete (1988)

Table A1 (Cont.)

Bands/indices	Description	Wavelength/ formula	Reference
EVI	Enhanced Vegetation Index	(2.5 * ((NIR – Red)) / (NIR + 6 * Red – 7.5 * Blue + 1))	Huete et al. (1997)
NDWI	Normalized Difference Water Index	(Green – NIR) / (Green + NIR)	McFeeters (1996)

CHAPTER 4: EVALUATION OF VOLUNTARY ADOPTION OF COVER CROPS AND ASSOCIATED CROP ROTATIONS USING REMOTE SENSING

Abstract

This study examines the voluntary adoption of winter cover crops and their associated crop rotations in the Mississippi Alluvial Plain (MAP) region. Cover crop locations are identified using remote sensing technologies, ground-truthed government data sources, and the United State Department of Agriculture's Cropland Data Layer (CDL). This research aims to assess the current extent of cover crop adoption and understand which crop rotations are most common in their incorporation. While government-subsidized programs like EQIP and CSP provide financial motivation for adopting cover crops, many producers have internalized the holistic benefits of cover crops and voluntarily adopted them into their crop rotations as a sustainable soil management practice. Results revealed a 5.3% increase in total voluntary cover crop adoption in the study region from 2013 to 2019. The study findings indicate a distinct change in crop rotations from 2013 to 2019, increasing the use of cover crops in cash-crop rotations. The analysis also revealed four predominant crop rotations that implement cover crops, with the soybean - cover crops - soybean pattern being the primary rotation with the largest implementation area. These findings provide valuable insights for policymakers and stakeholders to promote sustainable agricultural practices, foster further adoption of cover crops, and optimize cover crop integration into cropping systems in the MAP region.

Keywords: voluntary adoption, winter cover crops, cropping patterns, cropping sequence, soil organic carbon, Mississippi Alluvial Plain

4.1 Introduction

Winter cover crops provide benefits such as maintaining soil health, mitigating soil erosion, and improving nutrient retention in agricultural fields between primary cropping seasons (Adetunji et al., 2020; Basche et al., 2016; Dabney et al., 2001). Similarly, in the Mississippi Alluvial Plain (MAP), cover crops offer long-term benefits to producers by enhancing soil structure, increasing soil organic matter, and mitigating nutrient losses from leaching and/or runoff (Aryal et al., 2018; Kladivko et al., 2014). The MAP region is of significant national importance due to its extensive agricultural productivity and ecological significance. It encompasses parts of several states in the southern United States, including Arkansas, Mississippi, Louisiana, Missouri, and Tennessee. The region's fertile soil and favorable climate make it a productive agricultural area known for rice, soybeans, cotton, and corn production. In the American Corn Belt, the adoption of wintertime cover crops has experienced a significant increase of 2.3 million acres between 2006 and 2018, typically in a corn-soybean rotation (Geosolutions et al., 2019). The growth can be partially attributed to the financial incentives provided by the United States Department of Agriculture's Natural Resources Conservation Service (NRCS). Programs such as the Environmental Quality Incentives Program (EQIP) and Conservation Stewardship Program (CSP) have stimulated cover crop adoption. These federally funded programs have led to a 50% increase in the reported cover crop area in the United States between 2012 and 2017 (Wallander et al., 2021).

Despite the substantial government expansion in funding for incentives to encourage producers to adopt cover crops since 2012 (Wallander et al., 2021), the voluntary (non-government subsidized) adoption of cover crops remains unknown due to challenges in obtaining ground-truthed, spatial data, and a reliable method for identifying voluntary adoption. This study addresses these gaps by investigating the voluntary adoption of cover crops in the MAP and examining producers' crop rotations before and after implementing cover crops. Additionally, this research explores the potential environmental benefits of total model-predicted (government-funded vs. voluntary) cover crop adoption regarding estimated, potential soil organic carbon (SOC) sequestration, which plays a crucial role in enhancing soil health, mitigating climate change, and improving the overall sustainability of agricultural systems (Qin et al., 2023).

To estimate the adoption of voluntary cover crops and associated SOC sequestration, remote sensing data from Landsat 8, the USDA-Cropland Data Layer (CDL), and the Google Earth Engine (GEE) platform were used. This approach identified specific locations of wintertime cover crops in the MAP region from 2013 to 2019 (Ahmed et al., 2023). In the past decade, particularly after 2010, the utilization of remote sensing technologies has played a crucial role in effectively identifying the location and extent of wintertime cover crops across the United States (Hively et al., 2015; Kc et al., 2021; Thieme et al., 2020). One of the current study's goals was to identify government-subsidized cover crops and estimate the areas of voluntary cover crops in the MAP region. The study aimed to leverage the identified wintertime cover crop location data, combined with government-subsidized cover crop acreage data from EQIP and CSP programs and USDA's CDL, to estimate voluntary adoption of wintertime cover crops and their respective crop rotations. With a better understanding of the crop rotations most conducive for cover crop adoption, future government funding to incentivize cover crop adoptions can better target those producers with the greatest likelihood of adoption.

Crop rotations/patterns and/or sequences implemented by producers before and after wintertime cover crop adoption are important to policy research and agricultural planning to better understand the relationships between cropping patterns and ultimately cover crop adoption. The decision-making process between crop rotations and cover crops is interrelated at the farm level (Dury et al., 2012). In many parts of the MAP region, cash crops are followed by wintertime cover crops to improve soil health, control pests, and reduce weed populations (Bergtold et al., 2019). Cover crop adoption is affected by the difference in timing before and after specific cash crops are harvested or planted (Wallander et al., 2021). Both late and early harvesting of cash crops may increase the duration of the cover crop season, which can also facilitate the potential use of a cover crop. What is currently unknown is which crop rotations will most likely include a cover crop between cash-crop production cycles in the MAP region. Merely estimating the overall extent of cover crop acreage is insufficient because it gives no insight into how cover crops fit into cropping patterns. It is important to better understand the specific crop rotations where cover crops are being implemented to enhance their adoption rates on a broader scale. To our knowledge, no prior research has been undertaken to specifically identify how cover crops fit into cropping patterns using remote sensing techniques in the MAP region and across the continental United States. This study's findings will provide valuable information to policymakers and agricultural stakeholders in an attempt to optimize cover crop adoption and improve agricultural practices in the MAP region and beyond.

This study provides a foundational basis for evaluating government-subsidized cover crop adoption programs. The rapid data collection approach introduced in this study can be replicated in other areas, assisting researchers and policymakers in their investigations into cover crops and conservation (Dalsgaard, 2013; Park et al., 2022). The potential of cover crops to contribute to carbon sequestration initiatives is a promising development, potentially leading to an increase in their voluntary adoption by farmers who see the dual benefit of soil conservation and the possibility of additional revenue from carbon credits (Plastina & Sawadgo, 2021;

Plastina & Wongpiyabovorn, 2023). The emerging voluntary carbon markets within the agricultural sector could provide additional financial incentives for implementing conservation practices, such as cover cropping, beyond government funding through programs such as EQIP and CSP. As large corporations seek to meet net-zero emission targets, agricultural carbon credits offer an appealing solution. The ability of cover crops to sequester atmospheric carbon positions producers as essential contributors to these carbon offset initiatives (Bowman & Lynch, 2019). A better understanding of how cover crops fit into crop rotations may allow government programs and private industry to target specific types of row crop producers for potential carbon credits.

4.2 Materials and methods

4.2.1. Study Area

The focus region for this research is the Arkansas portion of the Mississippi Alluvial Plain (MAP) region, which includes the entirety or parts of 27 counties (Fig. 1). This study region is considered one of the most agriculturally productive regions in the United States because of its fertile soil that supports large-scale agricultural production. Many producers in the study area have voluntarily planted various types of winter cover crops, and some have taken advantage of government assistance via programs like CSP and EQIP to enhance soil quality and reduce soil erosion. Gaining a comprehensive understanding of the voluntary adoption of cover crops and identifying cropping patterns is essential for producers and policymakers.

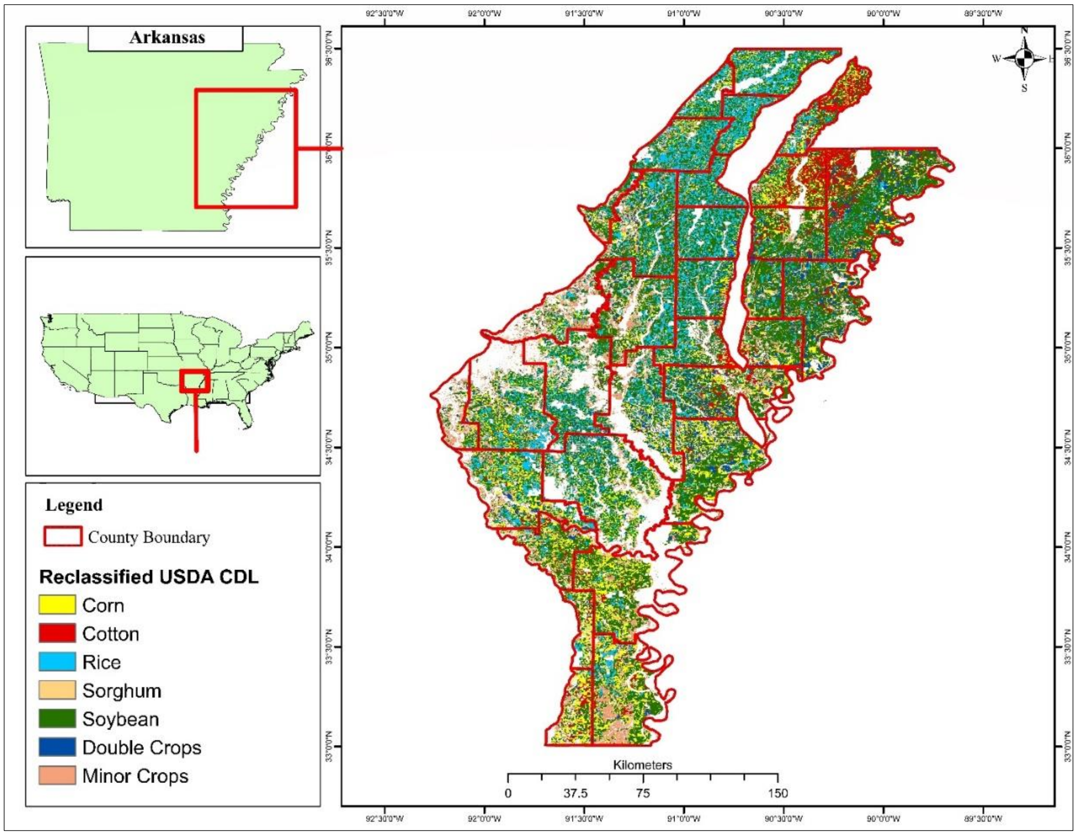

Fig. 1: Mississippi Alluvial Plain (MAP) region used in the study. Note that an example of a 2013 reclassified USDA CDL data is presented here for reference.

4.2.2. Data

The data utilized in this study were derived from various sources, including remote sensing data, government-subsidized cover crop data, model-predicted cover, and non-cover crop areas, and USDA-CDL data layers. To identify the voluntary adoption of cover crops at the county level, total model-predicted wintertime cover crop county-level acreage data in conjunction with total government-subsidized cover crop acreage data from NRCS from 2013 to 2019 were used. The process for mapping the voluntary adoption of cover crops is detailed in section 4.2.4. Reclassified CDL data was combined with the model-predicted cover and non-cover crop areas data to identify cropping rotations. The CDL product provides an annual, geo-referenced land cover map for the continental United States, encompassing 133 different crops and non-crop raster data. The CDL data for multiple years (2013 to 2020) were sourced from the GEE data catalog. To streamline the analysis, a GEE script was employed to reclassify the crop types from the CDL into seven major classes (Fig. 1 illustrates an example of the reclassified CDL). For this study, five major CDL crop categories: corn, cotton, rice, sorghum, and soybeans, were selected, as these are the predominant cash crops in the MAP region. Additionally, four double crop pixels (i.e., double crop winter wheat/soybeans, double crop winter wheat/corn, double crop winter wheat/sorghum, and double crop winter wheat/cotton) were combined into a single, double crop category, with all remaining pixels falling into the “Minor Crops” category. Corn, rice, cotton, soybean, and sorghum are the main cash crops grown in eastern Arkansas, all of which are generally cropped with traditional tillage practices. In the subsequent analysis and visualization, the primary focus of this study was on soybean, cotton, and corn, as they represent the primary crop sequences involving cover and non-cover crops in the MAP study area. Despite rice being a significant crop in the MAP study area, it is typically not integrated with cover crops for various reasons. Rice cultivation primarily occurs on poorly drained soils, leading to waterlogged conditions during winter. This limits cover crop survival due to excessively wet or flooded soils. Additionally, some rice fields are intentionally flooded during winter to create a habitat for ducks, further limiting the feasibility of establishing cover crops. These factors contribute to the exclusion of rice from the subsequent analysis. Furthermore, the initial analysis revealed limited acreage for rice, sorghum, and double crop systems within cover crop fields. Consequently, these categories were combined under the "Other Crops" which includes “Minor Crops” as well. Consequently, these categories were combined under the "Other Crops" category only for visualizations for CDL Cash Crops > Cover Crops (sections 4.2.5.1) and Cover Crops > CDL Cash Crops (sections 4.2.5.2).

4.2.3. Identification of cover and non-cover crop areas

Agricultural crop mapping and acreage estimation are challenging given the diverse farming systems, varying field sizes/ boundaries, crop heterogeneity, and heterogeneity in objectives across land management systems (Liu et al., 2020). Despite these challenges, such mapping remains a vital prerequisite to identifying agricultural farms, their respective crops, and their spatial distribution (Hudait & Patel, 2022). The USDA-NASS combines remote sensing and field-based data to map and estimate crop acreage. They generate a range of products, such as the Cropland Data Layer (CDL), for public usage. However, the CDL database has limited information concerning winter cover crops, particularly their spatial and temporal distribution, creating difficulties for researchers and policymakers.

There is currently a lack of data regarding planted cover crop acreage and voluntary cover crop adoption in the U.S. Such data is essential to understanding the 'additionality' and 'spillover effects' of government cost-shared funding on cover crop adoption over time and identifying factors and crop rotations that could encourage farmers to adopt cover crops independent of government funding (Mezzatesta et al., 2013). To address the data gaps and generate new information for the MAP study region, Landsat 8 satellite images were combined with yearly USDA-NRCS cover crop location data, serving as training data for the random forest machine learning model. This model was implemented using Google Earth Engine (GEE), enabling the identification and mapping of cover crop and non-cover crop areas, along with their corresponding acreage, over seven years.

The USDA-NRCS government cover crop dataset along with the NASA Landsat 8 Operational Land Imager (OLI) Top of Atmosphere (TOA) 30-m spatial and 16-day temporal resolution remote sensing, and CDL data was used to identify and map wintertime cover crops in the MAP study region from 2013 to 2019 (Ahmed et al., 2023). Following Ahmed et al. (2023), a pixel-based method was employed to distinguish between pixels associated with cover crops and those not. The methodology for identifying cover and non-cover crop areas consisted of three steps. Initially, the ground-cover months for the cover crop were identified, which extended from November to March. Next, cloud cover was eliminated from the Landsat satellite data. Finally, a machine learning algorithm was utilized to identify the cover crop, employing multiple spectral reflectance bands and indices. The USDA-NRCS cover crop ground-truthed data were split into training (70%) and validation (30%) sets for the final classification. This classification process was performed using the GEE platform. The nonparametric Random Forest (RF) machine learning classifier was employed to categorize the final image composites into a binary - cover crops and non-cover crop areas (Kc et al., 2021; Ok et al., 2012; Pal, 2005). A limitation encountered while using the USDA-NRCS database was the occasional lack of GPS accuracy for specific cover crop locations. This issue arises when producers record their GPS location from their home or farm shop rather than the actual site of the cover crop cultivation on their farm. A rule or threshold-based approach for filtering cover crop point data was employed to overcome this problem and ensure quality training data for machine learning models, as Ghazaryan et al. (2018) suggested. Locations within cover crop fields were filtered and pinpointed by applying an NDVI threshold value greater than 0.3, aligning with prior studies' methodologies (Hively et al., 2015; Kc et al., 2021; Thieme et al., 2020). Using the GEE platform, pixels with an NDVI value exceeding 0.3 were classified as cover crops.[1] In contrast, pixels falling below this value were

[1] For this analysis, it was assumed that winter wheat was a cover crop, not for grain, within the MAP study area since specific cover crop information was unavailable from the USDA-NRCS dataset. To estimate how this assumption may affect the results (quantifying total cover crop area), the USDA-NASS data on winter wheat harvested for grain in Arkansas was used as a proxy. This allowed the calculation of the percentage of winter wheat for grain by dividing the USDA-NASS winter wheat area harvested yearly by the area of total cropland. The findings indicate that only a small yearly percentage (ranging from 0.8% to 9.7%) of the winter wheat for grain may have been identified in the model as a cover crop.

categorized as "non-cover crop" pixels. This non-cover crop category encompasses bare soil areas, farm-built zones, shallow and sparse vegetation (NDVI < 0.3), winter weeds, and some non-green crop residue pixels. By leveraging the CDL cultivated data layer to exclude non-cultivated fields, a significant portion of these non-cover crop pixels were ensured to represent bare soil areas or fallow lands, thereby enhancing the accuracy of the classification process. Finally, the classified map data were exported and processed using ArcGIS and R-Studio for visualization and subsequent analysis. In adherence to USDA-NRCS data sharing agreements and to ensure data privacy, acre ranges were aggregated at the county level for subsequent mapping activities.

4.2.4. Voluntary cover crop adoption

While several programs like CSP and EQIP subsidize producers to grow cover crops and participate in conservation efforts, not all producers who adopt cover crops receive government support for adoption (Dunn et al., 2016). To identify the voluntary adoption of cover crops at the county level, the total model-predicted wintertime cover crop location data and the USDA-NRCS total county-level acreage data for government-subsidized cover crops from 2013 to 2019 were utilized. The total model-predicted wintertime cover crop location data were aggregated at the county level for further analysis. Next, the difference was calculated between the total model-predicted cover crop acreage and the acreage of cover crops that received government subsidies. This calculation allowed the isolation and the identification of the voluntary adoption of cover crops in each county for each year of the study period. This methodology provided insights into the patterns and trends of voluntary cover crop adoption at the county level, shedding light on the role of government incentives in promoting cover crop adoption versus producers voluntarily adopting them.

4.2.5. Analysis of cover crop rotations

Different crop rotations for Arkansas's portion of the MAP were identified using multi-temporal satellite imagery capabilities. The large and exhaustive CDL crop-specific layer dataset contains information on 133 different crops and non-crop raster data. Utilizing this data would have resulted in 35,378 unique combinations of cropping rotations/patterns and/or sequences to analyze. The study focused on the reclassified CDL layer data to streamline the analysis process and account for limited acreage in other categories (as discussed in section 4.2.2). This specific dataset was chosen to facilitate a more manageable analysis of cropping patterns, allowing the efficient examination and interpretation of the data in subsequent steps. Specifically, the study focused on three cropping patterns revolving around cash crops and their sequential cultivation following cover and non-cover crops. These patterns include (1) finding which cash crops are planted prior to the planting of cover crops, (2) identifying which cash crops followed cover crops, and (3) mapping all potential cash-cover-cash rotations by area. This analytical undertaking employs classified cover and non-cover crops map data and the reclassified USDA-CDL data layers from 2013 to 2020.

4.2.5.1. Cropping pattern (CDL Cash Crops > Cover Crops)

An ArcGIS combine tool was used to identify crop rotations (which cash crops were planted before the cultivation of cover crops), with inputs consisting of reclassified CDL imagery of a specific year, succeeded by classified cover vs. non-cover crop imagery from that same year (Fig. 2). This manipulation resulted in the generation of 14 unique crop rotation patterns per year from 2013 to 2019.

Fig. 2: Example of CDL crops planted prior to cover and non-cover crop areas within the same year. CDL layer with multiple colors representing different reclassified crop types (left) and classification of binary cover and non-cover areas (right). The green regions represent model-predicted areas with cover crops, the yellow represent non-cover crop areas, while the white represent mask-out areas.

4.2.5.2. Cropping pattern (Cover Crops > CDL Cash Crops)

The same combination tool was applied to detect which cash crops followed cover crops. The initial input consisted of cover vs. non-cover crop imagery of a specific year, followed by reclassified CDL imagery of the following year (Fig. 3). This methodology allowed for a determination of which cash crops were grown after cover crops termination, generating another 14 unique crop rotation patterns per year from 2013 to 2020.

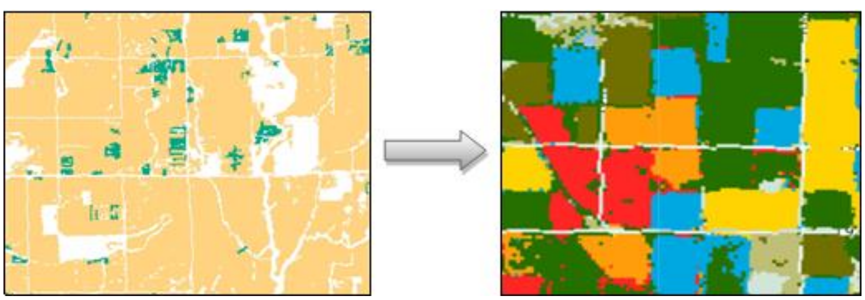

Fig. 3: Example of CDL crops planted after cover and non-cover crop areas in the following production year. Classification of binary cover and non-cover areas (left) and CDL layer with multiple colors representing different reclassified crop types (right). The green regions represent model-predicted areas with cover crops, the yellow represents non-cover crop areas, and the white represents mask out areas.

4.2.5.3. Crop rotations including cover crops (CDL Cash Crops > Cover Crops > CDL Cash Crops)

The final cropping pattern encompasses an entire crop rotation cycle. The analysis began with the CDL cash crops of 2013, used the cover and non-cover crops of the same year to evaluate which cash crop fields were sown to cover crops, and concluded with the CDL layer of 2014, and followed the same procedure for other study years (Fig. 4). This allowed the determination of which crop rotations were most frequently associated with the adoption of cover crops. As a result, 98 distinct cropping patterns were generated per year from 2013 to 2020.

Fig. 4: Example of cropping patterns depicting the sequence of CDL crops planted before cover and non-cover crop areas within the same production year and CDL crops planted after cover and non-cover crop areas in the following year. CDL layer with multiple colors representing different reclassified crop types in the previous year (left), classification of binary cover and non-cover areas of the same year (middle), and CDL layer with multiple colors representing different reclassified crop types in the following production year (right). The green regions represent model-predicted areas with cover crops, the yellow represents non-cover crop areas, and the white represents mask-out areas.

4.2.6. Soil organic carbon (SOC) sequestration estimation

The methodology used to estimate potential SOC sequestration through the adoption of cover crops incorporates several factors, such as total cover crop acreage, biomass allocation, residue cover thresholds, and carbon concentration in biomass. This estimation considered the total cover crop acreage across several years and delineated between government-funded and voluntarily adopted acreage.

Previous research has identified a variety of SOC sequestration rates associated with the adoption of cover crops, with these rates applicable to different soil depth intervals. For example, Poeplau and Don (2015) linked the use of cover crops to enhanced SOC sequestration and estimated a mean rate of 0.32 ± 0.08 Mg/ha/year (0.14 ± 0.04 tons/acre/year) at soil depth ranging from 0 to 30 cm. In contrast, Ruis & Blanco-Canqui, (2017) proposed a greater rate of 0.49 Mg/ha/year (0.22 tons/acre/year), applicable to a soil depth of 0-30 cm. Jian et al. (2020) suggested a rate of 0.54 Mg/ha/year (0.24 tons/acre/year), which applied to varying soil depths in the 0-30 cm range. It should be noted that these SOC sequestration rates, as mentioned in previous studies, primarily originated from global meta-analyses. However, it is important to recognize that SOC sequestration can vary significantly based on factors such as soil texture, agricultural management practices, elevation, climate, and location (Bai et al., 2019; Herzfeld et al., 2021; Lessmann et al., 2022).

Blanco-Canqui, (2022) discussed the effects of cover crops on SOC based on a review of studies conducted in the United States. The findings demonstrated that cover crops accumulated SOC between 0.2 and 0.92 Mg/ha/year (0.09- 0.41 tons/acre/year), with an average of 0.56 Mg/ha/year (0.25 tons/acre/year), in the 22 instances where cover crops increased SOC. On a broader set of 77 comparisons conducted for the upper 30-cm soil depth, cover crops accumulated SOC between 0 and 0.92 Mg/ha/year (0-0.41 tons/acre/year), with an average of 0.46 Mg/ha/year (0.21 tons/acre/year). Adding to the literature, Causarano et al. (2006) extensively analyzed 20 studies focusing on cotton production systems in the Southeastern United States. The review indicated that adopting no-tillage practices compared to conventional tillage led to an increase in SOC by an average of 0.48 ± 0.56 Mg/ha/year (0.21 ± 0.25 tons/acre/year). Moreover, integrating high-residue-producing crops such as corn and small grains into diverse crop rotations further augment SOC sequestration. Specifically, the combination of no-tillage practices with cover crops resulted in an average SOC sequestration rate of 0.67 ± 0.63 Mg/ha/year (0.30 ± 0.28 tons/acre/year), while employing no-tillage practices alone yielded 0.34 ± 0.47 Mg/ha/year (0.15 ± 0.21 tons/acre/year). This emphasizes the significant role that cover crops and tillage practices play in soil organic carbon sequestration.

These findings emphasize the potential of cover crops to sequester carbon within agricultural systems, contributing to improved soil health and environmental sustainability. Two principal carbon reservoirs exist within a landscape: biomass carbon, which is the carbon stored within live vegetation, and soil carbon, referencing the humified carbon portion of the soil. SOC sequestration was approximated using the total acreage of cover crops estimated within the study area via remote sensing methods and the USDA-NRCS database.

The aboveground (AG) and belowground (BG) biomass were estimated without specific cover crop species information. The AG biomass was assumed to be 2/3 of the total biomass (B), and the BG biomass was estimated to be 1/3 of B. These assumptions were applied to a conservative estimate of 3500 lbs/acre for AG and 1747 lbs/acre for BG (Brye, 2012; USDA-NRCS, 2018).

The total AG and BG biomass in tons/acre (T_AG and T_BG, respectively) were then calculated using the respective yearly cover crop acreage (CCA) and the conversion factor from lbs to tons [Equations 1 and 2]. The combined total of AG and BG biomass (T_AG&BG) was then calculated [Equation 3].

$$T\_AG = (AG * CCA)/2000 \quad \text{(Equation 1)}$$

$$T\_BG = (BG * CCA)/2000 \quad \text{(Equation 2)}$$

$$T\_AG\&BG = T\_AG + T\_BG \quad \text{(Equation 3)}$$

The assumption was made that 70% of the total aboveground biomass (T_AG) would be mixed into the soil (I_AG), leaving the remaining 30% as surface residue (P) to satisfy the USDA-NRCS guidelines for conservation tillage (CT) (Prabhakara et al., 2015) [Equation 4]. The 30% surface residue is the minimum threshold needed to qualify as CT. It is important to note that the estimated annual SOC sequestration rate might be higher than the actual rate. This is because CT practices can also include no-tillage (NT), where 100% of the crop residue remains on the surface. However, estimating the annual SOC rate from a range of surface residue coverage was beyond the scope of the study.

$$I\_AG = T\_AG * (1-P) \quad \text{(Equation 4)}$$

The total biomass in the soil (T_BS) was computed by summing I_AG and T_BG [Equation 5]. The total carbon input to the soil (C_S) from the cover crop biomass was then calculated by assuming a carbon concentration (C) of 50% (Popp et al., 2011) [Equation 6].

$$T\_BS = T\_BG + I\_AG \quad \text{(Equation 5)}$$

$$C\_S = T\_BS * C \quad \text{(Equation 6)}$$

The biomass carbon requires microbial processing to achieve humification, so a microbial efficiency (E) of 50% was assumed (Keiblinger et al., 2010; Saifuddin et al., 2019; Sinsabaugh et al., 2016). Based on this assumption, the total soil carbon after microbial processing (T_SCM) was calculated [Equation 7].

$$T\_SCM = C\_S * E \quad \text{(Equation 7)}$$

The final step involved calculating the SOC sequestration rate (R) tons/acre/year by dividing T_SCM by CCA [Equation 8].

$$R = T\_SCM / CCA \quad \text{(Equation 8)}$$

This approach, though mindful of uncertainties, aims to estimate the SOC sequestration capacity of cover crops conservatively. The accuracy and applicability of these estimations depend on various factors, including the quality and representativeness of the data used, specific conditions within the study area, and management practices. Thus, more research and validation are needed to refine the estimates and enhance the understanding of the actual impact of cover crops on SOC sequestration. This will allow for a more accurate depiction of SOC sequestration rates and how they may vary across different geographies, cover crop species, and management practices. Such research would contribute to optimizing sustainable agriculture practices and climate change mitigation strategies, further underlining the value of cover crops in achieving environmental sustainability, farm profitability, and soil health improvement.

4.3 Results and discussion

4.3.1. Voluntary adoption of cover crops

Both government-subsidized and voluntary cover crop adoption increased in the study area over time. According to NRCS provided data, the government-funded total cover crop acres were lowest in 2013 (9,617 acres) and remained low until 2017 (24,386 acres) but increased in 2018 (94,464 acres) and 2019 (201,361 acres) in the MAP region. The total voluntary adoption of cover crop acreage in 2013 was 667,655 acres and increased by 5.33% (35,608 acres) in 2019 (Fig. 5). The total cover crop acres that received government cost-sharing across all counties and years amounted to 402,839 acre-years. In contrast, the accumulated total of cover crop acres through voluntary adoption from 2013 to 2019 was estimated at 4,486,197 acre-years (Pearson's R=0.46, P=0.015). The fluctuations in cover crop acreage from year to year, observed in both government-subsidized and voluntary adoption, could be attributed to a combination of external factors. Notably, government-subsidized cover crop acreage in the study area saw a surge post-2013 and 2018, which may be related to policy changes. The Farm Bills of 2014 and 2018 likely played a role in this uptick as they provided farmers with financial incentives and technical assistance to adopt conservation practices, including cover cropping (USDA ERS, 2014, 2018). Additionally, it is worth noting that even farmers who are big supporters of cover crops might not use them on all their fields every year. Furthermore, due to variations in crop rotation and/or cropping patterns from year to year, there is not always a guarantee that cover crops will be present during the winter period. It is important to note that this study provides estimates and observations regarding the adoption of cover crops, but a definitive understanding of the reasons behind these fluctuations would require targeted surveys and interviews with farmers in both the government-subsidized and voluntary adoption categories.

These findings indicate a positive correlation between the amount of government cost-shared cover crop acres and the voluntary adoption of cover crops in the MAP counties. This signifies that in the study area, producers either voluntarily chose to adopt cover crops on their land without government assistance or subsidies, or there were cases where farmers had originally adopted cover crops with government support and chose to continue using them after the government assistance ended. Counties with higher government-funded cover crop acreage tend to have higher levels of voluntary adoption. This could have to do with similar cropping rotations in which producers (both those who are federally funded and who voluntarily adopted) would find cover crops beneficial. This finding suggests that the financial support provided through programs like EQIP and CSP may have played a role in encouraging increased adoption of cover crops, which is backed by previous literature (Mezzatesta et al., 2013; Sawadgo & Plastina, 2021). Furthermore, study results suggest the presence of "spillover effects" wherein the practices adopted by farmers benefiting from government programs could influence and inspire other farmers to adopt cover crops voluntarily.

However, it is important to note that the moderate correlation coefficient suggests that other factors may also significantly influence the voluntary adoption of cover crops. Therefore, further research is necessary to fully understand the factors involved in farmers' decision-making process regarding cover crop adoption.

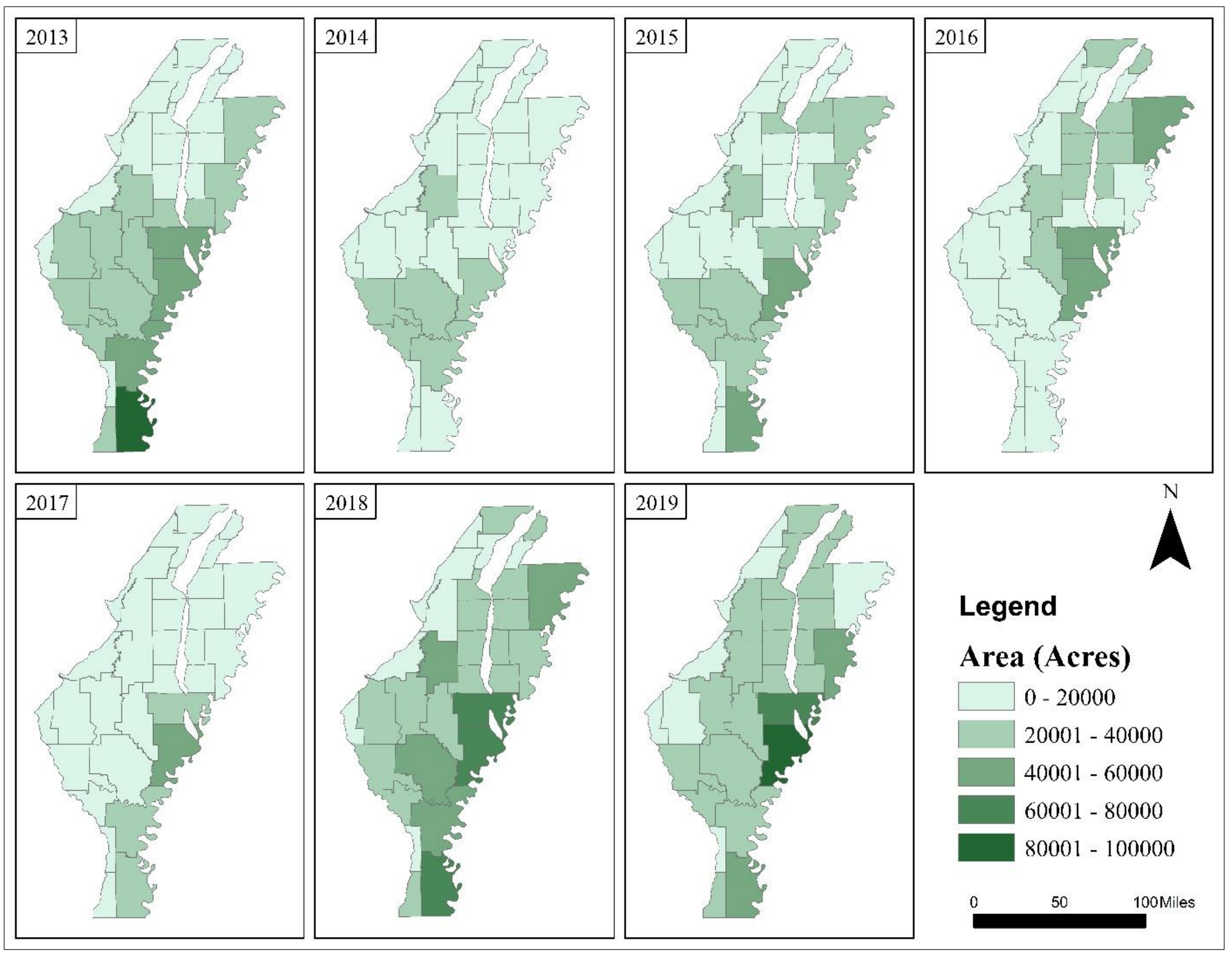

Fig. 5: Estimated voluntary cover crop adoption acres by county. Note: the lower right corner map represents the cumulative total of voluntary adoption of cover crop acres for all counties and years from 2013 to 2019.

Counties in the eastern section of the MAP region, especially those near the Mississippi River, exhibit a notable prevalence of cover crop adoption. This can likely be attributed to the kinds of crops typically cultivated in this region and the cropping rotations employed. For example, this area is renowned for its abundant production of soybeans, corn, and cotton. A study that spanned several states in the upper midwestern Mississippi River Basin found that 34% to 81% of agricultural land in select counties had the potential for integrating cover crops into corn and soybean crop systems (Kladivko et al., 2014). The study highlighted that changes in tillage practices might be necessary for this integration to occur, and greater use of no-till and mulch-till could further enhance adoption rates. Other potential contributing factors to cover crop adoption in the eastern MAP region include farmer conservation attitudes, regional climate conditions, local geographical features, agricultural market dynamics, incentive programs, and the influences of social networks. A wealth of research studies focusing on the Mississippi region have highlighted the advantages of integrating cover crops into these farming systems, notably enhancing soil health and mitigating soil erosion (Adler et al., 2020; Jacobs et al., 2022; Reba et al., 2020).

The government's support for environmentally conscious production practices and the interjection of government programs into subsidizing cover crops may have motivated farmers to embrace these practices voluntarily (Park et al., 2022). Voluntary adopters may have recognized the long-term benefits of cover crops regarding soil health, environmental conservation, and lowering farming expenses (Lee & McCann, 2019; Thompson et al., 2021). However, the complex and time-consuming application procedures and detailed record-keeping associated with government assistance and incentive programs may have discouraged many farmers from seeking financial support (Reimer & Prokopy, 2014).

This trend may highlight a growing awareness among producers regarding the potential benefits and value associated with cover crops. Producers could be motivated to voluntarily increase adoption, even without financial incentives. Moreover, producers may have come to realize that these practices, such as using cover crops, could contribute to carbon offset initiatives and potentially generate carbon credits, further adding to their appeal (Bowman & Lynch, 2019; Plastina & Sawadgo, 2021; Weinberg & Claassen, 2006; Winsten & Hunter, 2011). One significant aspect of this recognition is understanding the value of carbon sequestration in increasing SOC levels and its positive externalities for both the environment and the productivity of producers.

4.3.2. Adoption of cover crops on cash crop fields (CDL Cash Crops > Cover Crops) and (Cover Crops > CDL Cash Crops)

The dataset provides information on the area in acres and the percentage of cover and non-cover crops for the major cash crops, namely soybean, corn, and cotton, from 2013 to 2019. However, the analysis of this data reveals trends in the adoption of winter cover crops on these specific cash crops, shedding light on the evolving agricultural practices of producers (Fig. 6). The results indicate the adoption of cover crops in soybean production systems. In 2013, 4.63% of total MAP production acreage was under the cropping rotation of soybeans, followed by cover crops. Over the subsequent years, the percentage of soybean acreage planted with cover crops rose, reaching a peak of 8.07% in 2018, before declining to 5.75% in 2019. These findings indicate growth in the utilization of cover crops among soybean producers. Soybean cropping systems benefit greatly from cover crop use to keep soil in place because soybeans are generally considered a low-biomass-producing crop that does not return enough residue after harvest to provide adequate soil protection.

Likewise, the adoption of cover crops on corn fields has increased throughout the study. In 2013, cover crops were planted between corn crops, representing approximately 1.41% of the total cropland acreage. Over the study period, the corn acreage with cover crops increased, reaching 1.78% in 2019. Although the adoption rate of cover crops on corn fields remained lower than on soybeans fields, the findings suggest an increasing acceptance of this practice among corn producers. The increased adoption of cover crops on corn acres could be attributed to farmers' acknowledgment of the production advantages they provide specifically for corn cultivation. In contrast to soybeans, corn is a large biomass-producing crop, thus requiring greater soil manipulation by tillage to manage the greater amount of surface residue when no-tillage practices are not used, thus increasing the likelihood of soil disturbance and the potential for off-site soil transport. Consequently, cover crop use provides additional protection from potential soil erosion. In addition, as a crop that requires large fertilizer-N additions for optimal production, using legumes in a cover crop mix can increase soil N for subsequent crop use.

The adoption of cover crops on cotton fields also exhibited an upward trend, albeit with some variations. In 2013, cover crops accounted for 0.42% of the total cropland acreage; by 2018, this figure had risen to 2.71%. However, in 2019, the percentage of cotton acreage with cover crops decreased to 2.48%. The remaining crops from the dataset (including rice, sorghum, double crops, and other minor crops) have been combined into an "Other Crops" category to provide a comprehensive perspective. The adoption of cover crops on these crop fields displayed diverse patterns, ranging from low adoption rates to fluctuating trends. In 2013, the adoption rate for other cash crops was 4.34%, which decreased to 2.57% in 2014. However, there was a slight increase in adoption to 3.34% in 2015. In 2016, the adoption rate declined to 2.24%, followed by a further decrease to 0.8% in 2017. In 2018 a notable increase in adoption to 2.12% before experiencing a slight rise to 4.32% in 2019. These statistics highlight the varying trends in the adoption of cover crops among different types of cash crops. Further research and analysis are required to delve deeper into the specific dynamics and patterns of cover crop adoption in relation to other cash crops.

The adoption of winter cover crops has shown an increasing trend across the United States, according to the survey data analysis conducted by Wallander et al. (2021). Approximately 5 percent of corn acreage (as of 2016) had implemented cover crops, while the adoption rate was slightly higher for soybeans at 8 percent (as of 2018). As of 2015, the adoption rate of cover crops in cotton fields was roughly 13 percent. In contrast, corn-for-silage showed the highest cover crop adoption rate of nearly 25 percent (as of 2016). The findings align with the rising trend observed in this research regarding the adoption of cover crops, suggesting that farmers are increasingly aware of the potential benefits of their use.

While Fig. 6 highlights the importance of cover crops in rotation relative to the entire MAP region, it fails to highlight the relative importance of cover crops to individual cash crops. This is important to delineate as the acreage of individual cash crops fluctuates yearly. Fig. A1 in the appendix shows the temporal trend of the percentage of each crop in the MAP region, which was followed by a cover crop. In terms of total cash crop percentage followed by a cover crop, corn, and cotton have the highest percentage with a peak of 17% and 39%, respectively. While Figure 6 highlights the importance of total cover crops in soybeans, Figure A1 indicates that the maximum percentage of soybean area planted to cover crops after soybeans was 14%. Comparing Figures 6 and A1 highlights that while cotton may have less area planted to it in the MAP region, a higher percentage of total cotton acres are followed by a cover crop than soybeans for the four years of the study. Since cotton is a woody perennial, the residue left behind after harvest is typically low in quality. Cover crops diversify this residue's quality and augment the substrate quantity that enhances soil health and soil organic matter (SOM)

(Causarano et al., 2006). This substrate can boost soil health through SOC sequestration more quickly than without cover crops. Moreover, numerous cotton producers utilize cover crops to enhance soil moisture and conserve water during the cotton growing season. Fig. A1 is important for policy-making as it shows which type of crop is most likely to adopt cover crops in terms of percentage adoption, not total area of adoption.

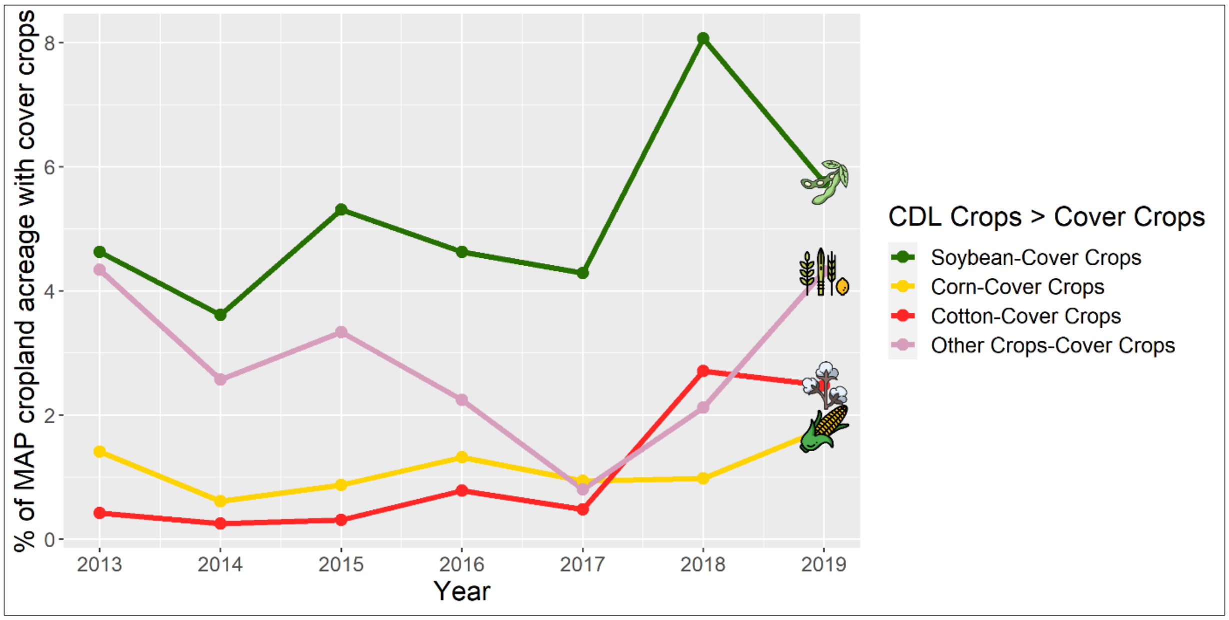

Fig. 6: Adoption of cover crops on major summer cash crop fields. Note: This figure illustrates the percentage of acreage with cover crop over time relative to the total MAP cropland area. The calculation considers the specific cash crop planted before the cover crops in the same fields.

Fig. 7 presents the type of cash crop which follows cover crop production, capturing the evolving trends over time. The dataset emphasizes the adoption rates of three major cash crops - soybean, corn, and cotton - following winter cover crops. Soybean fields that followed winter cover crops exhibited varying cover crop adoption rates across time. In 2013, soybean fields that succeeded winter cover crops accounted for 3.89% of the total cropland acreage. The proportion of soybean planting on cover crop fields fluctuated, reaching a peak of 5.99% in 2019. Still, a majority of soybean acreage does not involve the prior use of winter cover crops, suggesting the continued prevalence of conventional cropping practices and the land remaining fallow.

Similarly, corn fields that followed winter cover crops exhibited varying planting rates. In 2013, corn fields that followed winter cover crops comprised 0.52% of the total cropland acreage. Over time, the proportion of corn planting on cover crop fields gradually increased, reaching a peak of 1.62% in 2018. The planting of cotton following winter cover crops also displayed varying rates. In 2013, cotton fields that succeeded in winter cover crops comprised 0.47% of the total cropland acreage. Over the analyzed years, the proportion of cotton planting on cover crop fields gradually increased, reaching a peak of 2.99% in 2018. Based on the combined data for other cash crops, the “Other Crops” planting rate following winter cover crops exhibited variations over the years. In 2013, the planting rate was 5.95%, which decreased to 3.56% in 2014. It remained relatively stable at 3.44% in 2015 and declined to 2.73% in 2016. The planting rate showed a marginal rise to 1.53% in 2017. However, there was a significant surge in adoption in 2018, reaching 4.96%, followed by a slight decrease to 4.68% in 2019. These statistics illustrate the diverse planting patterns for "Other Crops" following winter cover crops, underscoring the need for further investigation to comprehensively understand the specific cropping sequences and factors influencing their incorporation.

Fig. A2 in the appendix shows the temporal trend of the percentage of each crop in the MAP region which followed a cover crop. Like the results in Figure A1, corn and cotton have the highest percentage of their relative crop following a cover crop with a maximum of 18% and 34%, respectively. This is important from a policy perspective, as Fig. A2 suggests that cotton and corn producers have higher adoption rates than soybean producers.

The analysis unveils varying planting rates of cash crops following winter cover crops, supported by findings from previous studies (Almoussawi et al., 2020; Marcillo & Miguez, 2017; Wauters et al., 2021; Wyland et al., 1996). The observed increasing trend in the incorporation of winter cover crops within soybean, corn, and cotton cropping systems demonstrates farmers' recognition of the potential benefits, including enhanced soil health and the promotion of sustainable agricultural practices (Blanco-Canqui et al., 2015; Kuo et al., 2001; Sarrantonio & Gallandt, 2003). Encouraging more comprehensive implementation of winter cover crops across these major cash crops can significantly contribute to agricultural systems' overall sustainability and resilience. However, further research is necessary to investigate the factors influencing adoption rates and evaluate the long-term impacts of integrating cover crops into cash crop rotations (Bergtold et al., 2012; Thompson et al., 2021).

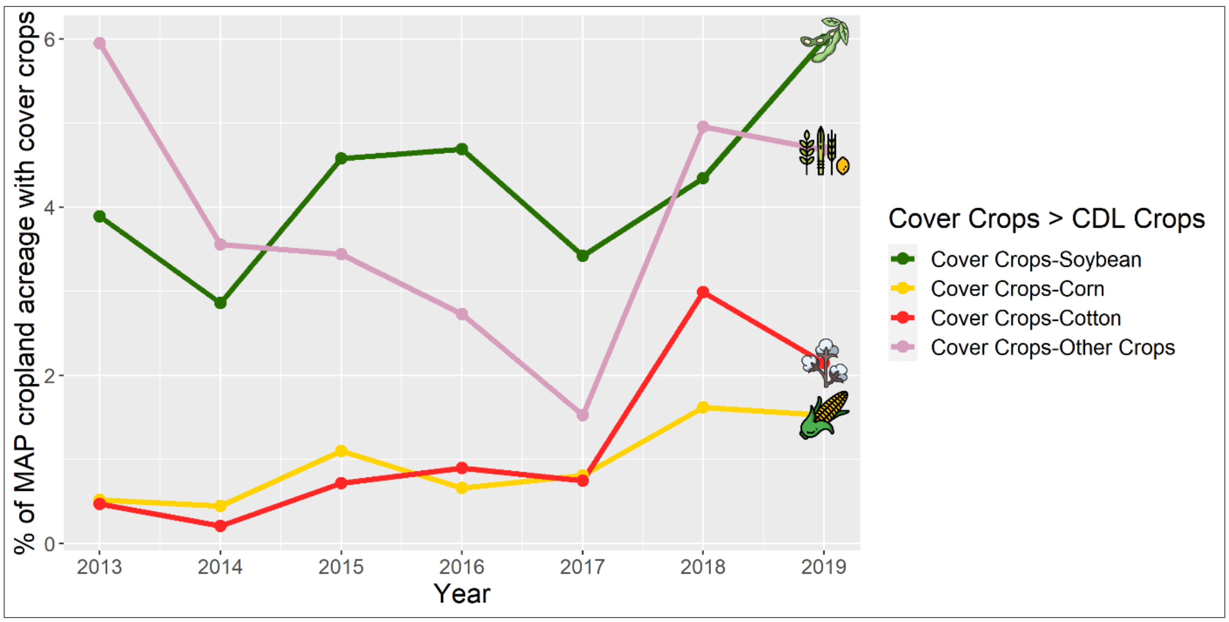

Fig. 7: Cash crop succession following winter cover crop fields. Note: This figure showcases the percentage of acreage with cover crop over time, meaning cash crops planted exclusively to winter cover crop fields in relation to the MAP total cropland area. The analysis considers the specific cash crops planted after the termination of winter cover crops in the same fields.

4.3.3. Analysis of cropping patterns (CDL Cash Crops > Cover Crops > CDL Cash Crops)

To investigate the dynamics of cropping patterns, an analysis was conducted on the cash crops planted before and after the winter cover crop between 2013 and 2019, as illustrated in Fig.

8. The results revealed changes in cropping sequences during this period, shedding light on the utilization of cover crops as an intermediate farming practice.

In 2013, the predominant cropping pattern involved the cultivation of soybeans-soybeans without the use of cover crops, which accounted for 20.7% of the total cropland area. Rice emerged as the second most prominent cash crop after the non-cover crop, accounting for 14.7% of the total cropland area. Other combinations of cash crops and non-cover crops, such as rice followed by soybean and corn followed by soybean, were also predominant cropping patterns, representing 10.2% and 7.1% of the total cropland area, respectively.

By 2019, there was a shift in crop rotations compared to 2013. Interestingly, the top 15 cropping systems were used on a smaller percentage of the total cropland area than in 2013. Soybeans, though were still the most common crop grown after non-cover crops, dropped to 17.95% of the cropland area, down from 20.72% in 2013. Rice, as well as combinations with soybeans and other non-cover crops, also saw a decline in the share of cropland. This decrease across the board suggests that farmers may have diversified their cropping patterns or possibly left more fields fallow during the summer. It also indicates that there could be a broader adoption of different systems that are not among the top 15, or that other factors were affecting planting decisions in 2019.

The emergence of cover crops between soybean production, denoted as "Soybean - Cover Crops - Soybean," accounted for 3.43% of the total cropland area in 2019, is noteworthy. Additionally, combining cover crops with other cash crops, such as "Minor Crops - Cover Crops - Minor Crops," represented 2.33% of the total cropland area, further illustrating the adoption of cover crops between different cash crops.

Figure 9 demonstrates the evolution of the adoption of cover crops between cash crops. Notably, there has been an increase in cropping pattern variations, particularly in 2018 and 2019. A total of four unique cropping patterns incorporating cover crops were identified, namely Cotton - Cover Crop - Cotton, Minor Crops - Cover Crop - Minor Crops, Soybean - Cover Crops - Minor Crops, and Soybean - Cover Crops - Soybean, with the latter being the most predominant pattern. It is worth noting that while cover crops are present between cash crops every year, Figure 9 does not report other crop rotations with cover crops due to their limited acreage. A separate analysis is presented in the appendix, focusing on adopting non-cover crops between cash crops each year (Appendix Fig. A3).

These findings indicate a shift in cropping patterns from 2013 to 2019, reflecting the increasing adoption of cover crops between cash crops. This trend signifies the evolving agricultural practices and the recognition of the numerous potential benefits of cover crops, including improved soil health and erosion control (Snapp et al., 2005). The observed changes in cropping patterns highlight the dynamic nature of the agricultural landscape in the MAP region, with farmers adapting their cash crop choices based on the presence of winter cover crops over time and the cash crops' prices. These shifts may be influenced by market demands, agronomic considerations, and policy changes (Zhou et al., 2022). Market demands can significantly shape cropping patterns as farmers respond to changing market conditions. Agronomic considerations such as soil fertility, pest management, and crop rotation also influence crop choices and the integration of cover crops. Farmers may adjust their cropping patterns based on the need to replenish soil nutrients, control pests, or break disease cycles.

Local, regional, or national policy changes can substantially impact cropping patterns (Chembezi & Womack, 1992). Government programs such as EQIP and CSP, incentives, or regulations that promote the adoption of cover crops or sustainable agricultural practices can influence farmers' decision-making processes. Likewise, changes in agricultural policies related to subsidies, crop insurance, or conservation programs can incentivize or discourage specific cropping patterns.

Understanding shifts in cropping patterns, including the increased adoption of cover crops, is crucial for stakeholders and policymakers in developing resilient and sustainable agriculture strategies. Recognizing the factors behind these changes allows for targeted interventions, such as financial incentives or educational programs, to foster sustainable farming practices. Collaboration between stakeholders like producers, researchers, and agricultural extension services in spreading information on cover crops' benefits can promote best practices, enhance knowledge-sharing, and facilitate implementation. This cooperative approach can augment agricultural systems' long-term viability and resilience. The evolving agricultural landscape reflects the acknowledged benefits of cover crops and sustainable farming. By comprehending these drivers, stakeholders and policymakers can devise strategies to ensure agriculture's enduring productivity and environmental sustainability.

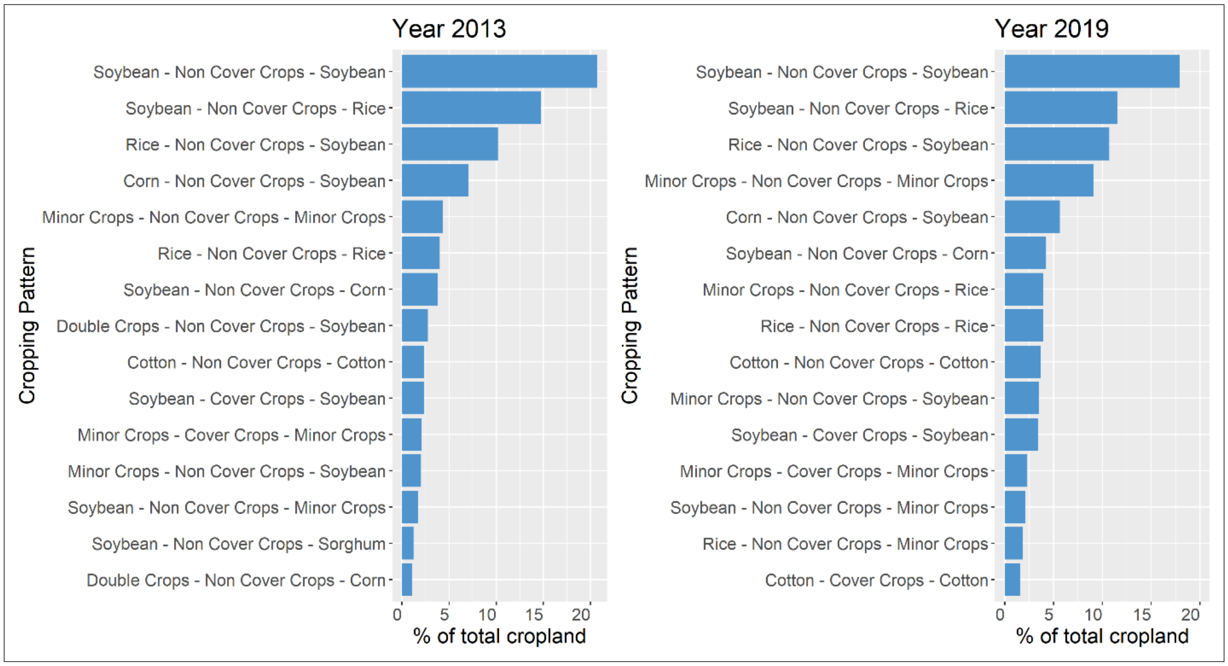

Fig. 8: Cropping patterns for 2013 and 2019- Cash crops planted before and after winter cover and non-cover crop (the top 15 cropping pattern combinations).

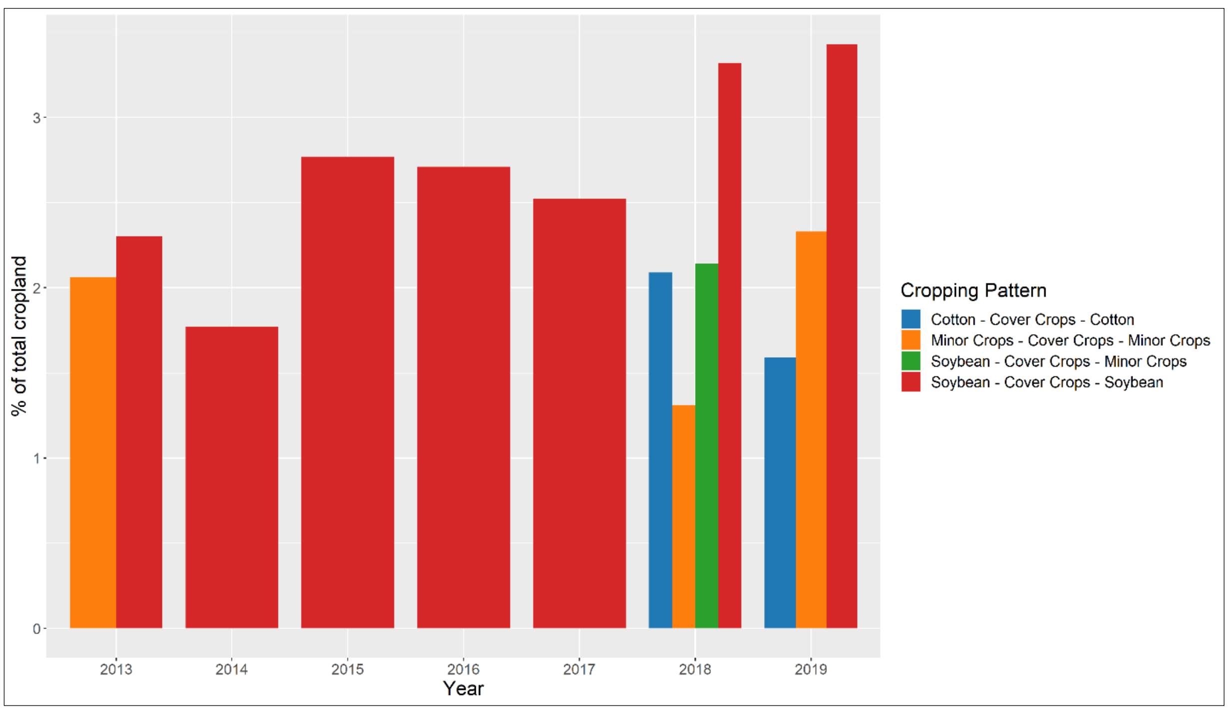

Fig 9: Percentage of total MAP area which consisted of crop rotations which included a cover crop from 2013 to 2019.

4.3.4. Estimation of SOC sequestration potential from cover crop acreage

The analysis of SOC sequestration potential resulting from cover crop adoption reveals variation across years (Table 1). In 2013, it was estimated that a total of 355,346 tons of carbon were sequestered from a combined (government-funded and voluntary adoption) cover crop area of 677,272 acres after accounting for biomass allocation, residue cover thresholds, and carbon concentration in biomass after microbial processing. The estimated SOC sequestration associated with cover crops significantly increased over time. The total SOC sequestration increased from approximately 355,346 tons in 2013 to 474,631 tons in 2019, indicating a 33.57% increase. Notably, the contribution from government cover crop acres to SOC sequestration rose steeply, from 5,046 tons in 2013 to a substantial 105,648 tons in 2019. The voluntary SOC sequestration experienced a marginal upward trend, rising from 350,300 tons in 2013 to 368,982 tons in 2019. This represents a notable but modest increase of approximately 5.3% over the seven years.

This study determined a conservative SOC sequestration rate of 0.52 tons/acre/year associated with cover crops in the MAP study area (Equation 1-8). This rate stands as a cautious approximation derived from the analyzed data. This process augments the soil's carbon content, enhances overall fertility, and strengthens the soil’s ability to maintain agricultural productivity. A more conservative estimate for potential SOC sequestration, derived from the work of Poeplau and Don (2015), has been reported at 0.14 tons/acre/year, as presented in Appendix Table A1 for readers to draw comparisons.

Table 1: Estimated Soil Organic Carbon (SOC) sequestration from cover crop adoption (2013-2019)

Year	Government CCA (acres)	Government SOC (tons)	Voluntary CCA (acres)	Voluntary SOC (tons)	Total CCA (acres)	Total SOC (tons)
2013	9,617	5,046	667,655	350,300	677,272	355,346
2014	18,758	9,842	421,908	221,363	440,666	231,205
2015	30,364	15,931	584,722	306,787	615,086	322,718
2016	23,889	12,534	537,644	282,087	561,533	294,621
2017	24,386	12,795	382,446	200,659	406,832	213,453
2018	94,465	49,563	785,720	412,245	880,185	461,808
2019	201,361	105,648	703,263	368,982	904,624	474,631

Note: Equation 1- 8 (section 2.6) was utilized to estimate the SOC sequestration values. The table only presents the total cover crop acres (CCA) and SOC tons value to ensure clarity and avoid excessive information.

It is important to note that including the model-predicted total cover crop acreage, assumed biomass allocation, residue cover thresholds, and carbon concentration in biomass used for calculating the SOC tons in this study was primarily intended to provide a conservative estimate for context rather than represent a definitive estimate. The sequestration potential can vary significantly due to specific crop types, management practices, climatic conditions, and numerous soil characteristics, namely texture (Bai et al., 2019; Herzfeld et al., 2021; Lessmann et al., 2022). Future research should incorporate site-specific data and consider these influential factors carefully to obtain more precise SOC sequestration estimations. By doing so, the accuracy and reliability of assessments regarding SOC sequestration in the context of cover crop adoption can be significantly enhanced.

Further research, incorporating more advanced modeling approaches and considering site-specific factors, is needed to obtain a more accurate assessment of SOC dynamics and the true potential of cover crop adoption for soil C sequestration (Poeplau & Don, 2015). Additionally, it is crucial to expand the analysis beyond SOC sequestration and consider the broader ecosystem benefits associated with cover crop adoption. Cover crops are vital in enhancing soil health, improving water quality, reducing erosion, and promoting biodiversity. Understanding the interconnections between these ecological processes and SOC sequestration will provide a more comprehensive evaluation of the overall impact of cover crop adoption on ecosystem services. However, at present, SOC sequestration is important to at least estimate due to its implication for C credits as a tradeable commodity in developing markets.

4.4 Summary and conclusion

The combination of environmental sustainability, potential financial incentives from carbon markets, and potential yield improvements make cover crops an increasingly compelling agricultural strategy for future sustainability. The findings reveal an increasing trend in cover crop adoption through government subsidies and voluntary initiatives. Despite mapping and data availability challenges, remote sensing technologies and government data sources provided valuable information for analyzing cover crop adoption at the county level. The analysis of major summer cash crops demonstrated the growing recognition of the benefits associated with cover crops, with soybean fields leading the adoption. The study also revealed changes in cropping patterns over time, with increasing incorporation of cover crops between cash crops.

Estimating SOC sequestration potential from cover crop adoption highlights some of the environmental benefits of these practices. Although the estimations provide an approximate assessment, they underscore the potential of cover crops to contribute to carbon offset initiatives and promote sustainable farming systems. Future research should incorporate site-specific data and consider important factors to obtain more precise SOC sequestration estimations.

The study's findings provide valuable insights for policymakers and stakeholders in developing strategies to support sustainable and resilient agricultural systems. By promoting cover crop adoption and optimizing cropping patterns, the agricultural sector can enhance soil health, mitigate erosion, improve water quality, and contribute to carbon sequestration. Collaborative efforts between policymakers, researchers, agricultural extension services, and farmers are essential to disseminate information, provide technical support, and maximize the benefits of cover crops. This holistic approach will contribute to the long-term viability, productivity, and environmental sustainability of the agricultural sector in the MAP region and beyond. Continued research in this area will be essential for understanding and maximizing the benefits of cover-crop systems for individual producers and broader environmental health.

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Appendix

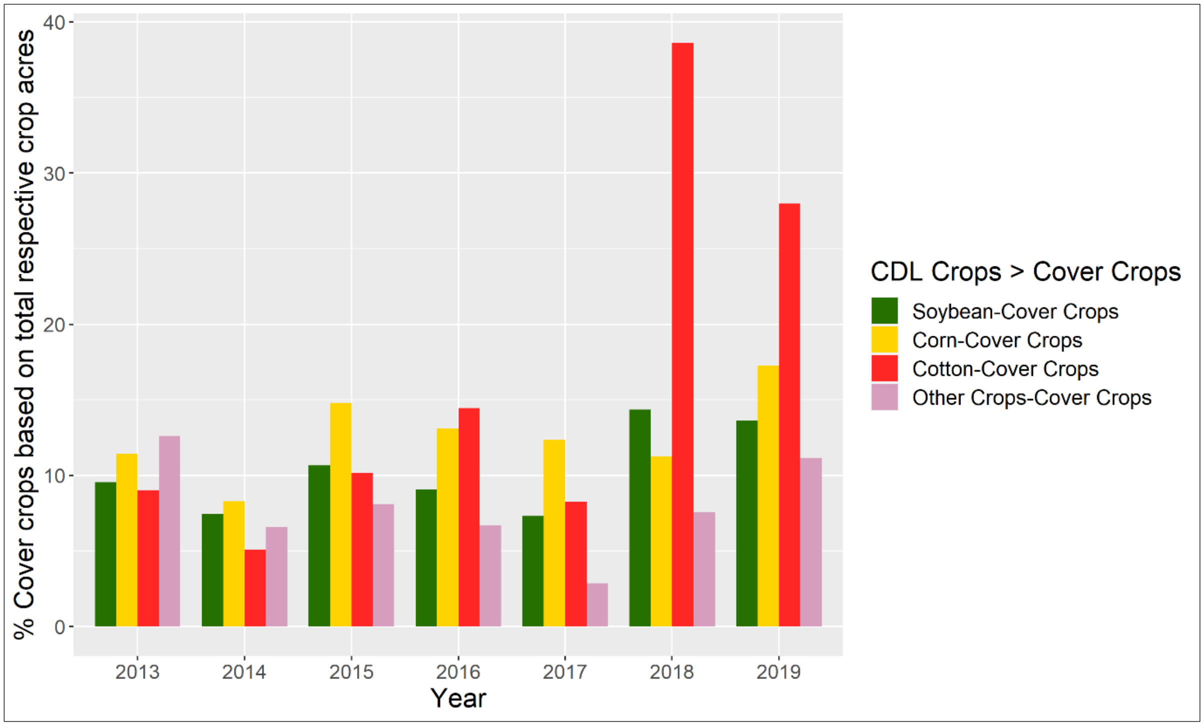
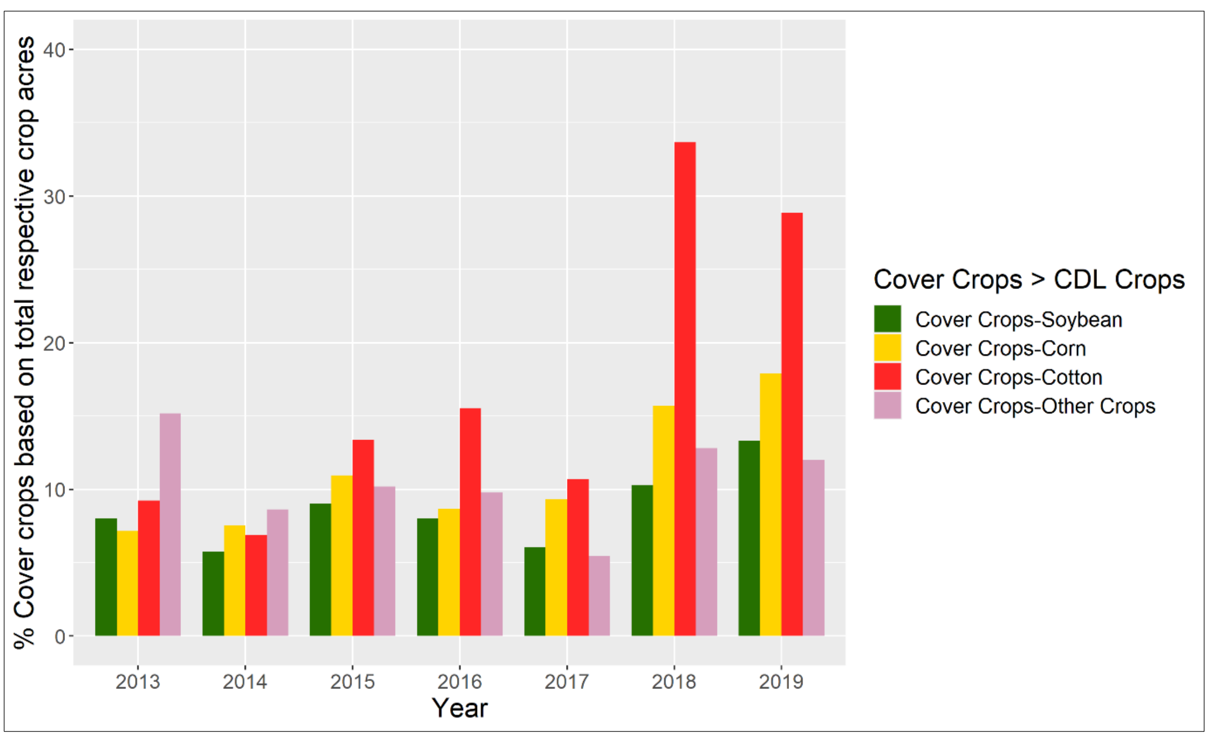


Fig A1: Temporal trend of the percentage of each crop in the MAP region, which was followed by a cover crop.



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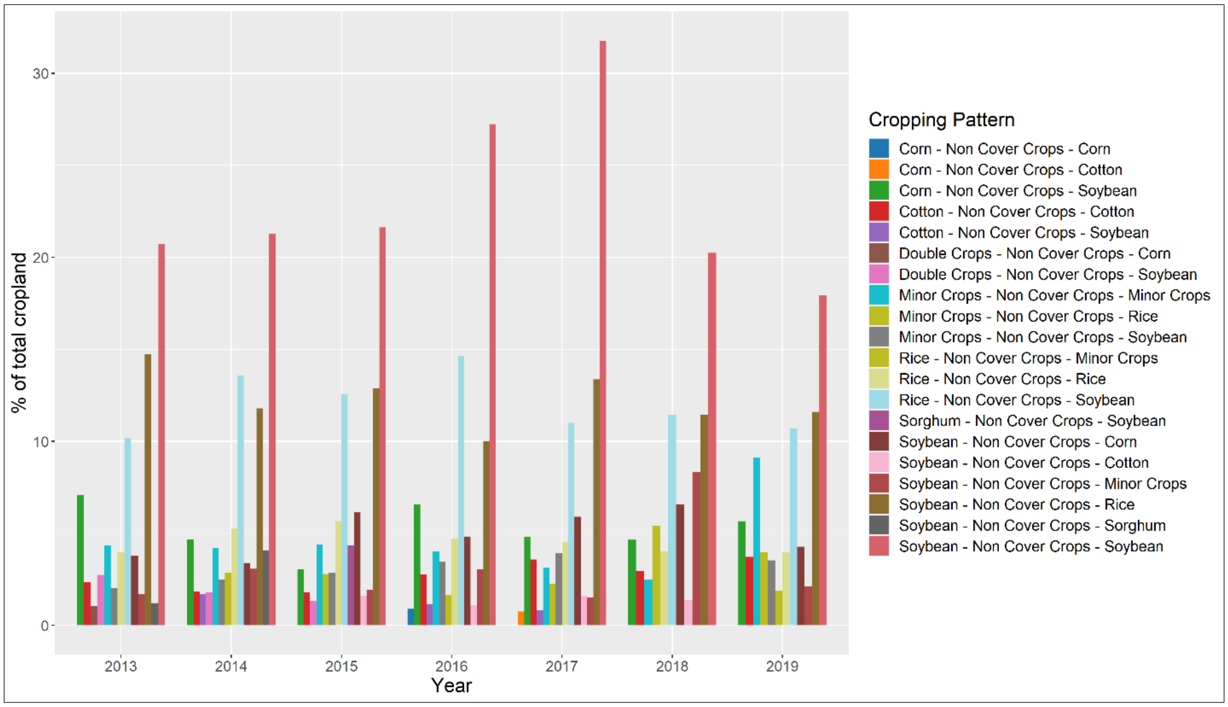

Fig. A3: Change in cropping patterns from 2013 to 2019, specifically highlighting the adoption of non-cover crops between cash crops. The figure highlights the most prevalent patterns that incorporate non-cover crops, based on the analysis of the top 15 cropping pattern data per year.

Table A1: Estimated Soil Organic Carbon (SOC) sequestration from cover crop adoption (2013-2019) using a conservative SOC estimate of 0.14 tons/acre/year.

Year	Government CCA (acres)	Government SOC (tons)	Voluntary CCA (acres)	Voluntary SOC (tons)	Total CCA (acres)	Total SOC (tons)
2013	9,617	1,346	667,655	93,472	677,272	94,818
2014	18,758	2,626	421,908	59,067	440,666	61,693
2015	30,364	4,251	584,722	81,861	615,086	86,112
2016	23,889	3,345	537,644	75,270	561,533	78,615
2017	24,386	3,414	382,446	53,543	406,832	56,956
2018	94,465	13,225	785,720	110,001	880,185	123,226
2019	201,361	28,191	703,263	98,457	904,624	126,647

CHAPTER 5: SUMMARY, CONCLUSION, AND RECOMMENDATIONS

This dissertation focused on the application of remote sensing technologies in the context of conservation agriculture. The research aimed to examine thematic research, development, and trends in remote sensing applied to conservation agriculture, identify and map winter cover crops using a remote sensing-based methodological framework, and assess voluntary cover crop adoption and cropping patterns in Arkansas's portion of the Mississippi Alluvial Plain (MAP) region.

The examination of thematic research in Chapter 2 revealed a growing research interest in the application of remote sensing in conservation agriculture over the past three decades. The analysis highlighted pixel-based classification methods and the prevalence of spectral indices in identifying agricultural conservation practices. The findings provided valuable insights into the potential of remote sensing for improving conservation agriculture and identified future research needs.

In Chapter 3, a remote sensing-based methodological framework was developed to identify and map winter cover crops. The framework utilized the Google Earth Engine platform, a Random Forest classifier, and Landsat 8 satellite data to achieve high classification accuracy. The analysis demonstrated an increase in model-predicted cover crop adoption over the study period, showcasing the framework's effectiveness in generating new and rapid cover crop data. Additionally, the study explored spectral indices and temporal profile analysis to assess cover crop phenological characteristics.

Chapter 4 focused on assessing voluntary cover crop adoption and cropping patterns in the MAP. Integrating remote sensing technologies, government data sources, and the USDA Cropland Data Layer, the study identified the voluntary adoption of winter cover crops and evaluated associated cropping rotations. The findings revealed an increasing trend in cover crop adoption, with soybean production being the predominant adoption area. The analysis also highlighted changes in cropping rotations over time, emphasizing the potential for integrating cover crops into agricultural systems for soil health and environmental benefits.

Overall, this research contributes to understanding the role of remote sensing in conservation agriculture. The findings underscore the potential of remote sensing technologies for improving the identification and mapping of conservation practices, monitoring cover crop adoption, and optimizing cropping patterns. These insights can inform policymakers, researchers, and stakeholders in developing strategies and programs to promote sustainable agricultural practices and enhance environmental stewardship.

For future research, it is recommended to explore further and refine remote sensing techniques for conservation agriculture, considering factors such as site-specific data, influential factors affecting carbon sequestration, and improved estimations of soil organic carbon. Collaboration among researchers, policymakers, agricultural extension services, and farmers is crucial for disseminating information, providing technical support, and maximizing the benefits of cover crops. Continued efforts in promoting cover crop adoption and optimizing cropping patterns will enhance soil health, mitigate erosion, improve water quality, and contribute to carbon sequestration, thereby ensuring the long-term viability and sustainability of the agricultural sector.

Overall, this dissertation has contributed to the advancement of remote sensing applied to conservation agriculture and provides a foundation for further research and policy development. The findings and recommendations presented here serve as a resource for scholars, researchers, policymakers, and stakeholders interested in conservation agriculture and its implementation.

Policymakers can make informed decisions and develop effective strategies to promote sustainable agricultural practices by leveraging remote sensing technologies. Researchers can further explore and refine remote sensing techniques, expanding their application to other regions and agricultural systems.

In conclusion, this dissertation has comprehensively analyzed remote sensing applications in conservation agriculture. The systematic review highlighted the increasing interest in remote sensing technologies for conservation practices. At the same time, the methodological framework demonstrated the effectiveness of remote sensing in identifying and mapping winter cover crops. The assessment of voluntary cover crop adoption and cropping patterns offered insights into the current extent of cover crop use and its potential for expansion.

Based on the findings, several recommendations can be made for future research and policy development:

1. Foster collaboration and knowledge exchange: Encourage collaboration between researchers, policymakers, agricultural extension services, and farmers to share knowledge, experiences, and best practices related to conservation agriculture and remote sensing technologies. This collaboration can enhance the adoption and implementation of sustainable agricultural practices.
2. Enhance data availability and accessibility: Improve access to remote sensing data, including satellite imagery, spectral indices, and other relevant datasets, to facilitate research and monitoring of conservation agriculture practices. Open data initiatives and partnerships with satellite providers can help overcome data limitations and support evidence-based decision-making.

3. Develop tailored tools and guidelines: Create user-friendly tools and guidelines that enable farmers and agricultural stakeholders to use remote sensing technologies for conservation agriculture effectively. These tools should provide practical insights and recommendations for cover crop adoption, cropping patterns, and soil health management.
4. Invest in capacity building: Promote training programs and workshops to enhance the technical expertise of researchers, policymakers, and producers in utilizing remote sensing technologies for conservation agriculture. This investment will empower stakeholders to harness the full potential of remote sensing data and tools.
5. Conduct site-specific studies: Conduct more site-specific studies to understand the regional variations in cover crop adoption, cropping patterns, and their impacts on soil health and ecosystem services. This localized knowledge will enable tailored interventions and strategies for different agricultural regions.
6. Integrate socio-economic analysis: Combine remote sensing data with socio-economic indicators to assess conservation agriculture practices' economic viability and social acceptance. This integrated analysis will help identify barriers and incentives for farmers to adopt cover crops and implement sustainable farming systems.

By implementing these recommendations, policymakers, researchers, and agricultural stakeholders can further advance the adoption of conservation agriculture practices and leverage the power of remote sensing technologies for sustainable land management. The findings and insights from this dissertation serve as a valuable resource for guiding future research, policy formulation, and on-the-ground interventions in conservation agriculture.