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Review

Current remote sensing applications for sustainable agricultural transitions and nature-based solutions

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ABSTRACT

The utility of remotely sensed data is becoming increasingly relevant for agroecological studies and practical agricultural applications, promoting a more sustainable development. Advancements in satellite technology continue to progress, offering higher spatial resolutions, a greater variety of sensors, and improved temporal frequencies. These developments enhance the accessibility and applicability of remote sensing data, enabling more precise monitoring of agricultural systems and providing new perspectives for implementing more efficient, environmentally friendly practices. This review aims to present a selection of current remote sensing applications in agriculture, with a focus on their potential to facilitate a transition towards more sustainable management practices. A systematic approach was used to identify, select, and synthesize relevant studies that demonstrate different applications of remote sensing methods in agriculture. The selected studies were examined within three key areas of sustainable agricultural management: i) nutrient management, ii) the environmental impacts of production, and iii) food security. The findings highlight that while remote sensing technologies offer valuable insights into agricultural sustainability, challenges remain in terms of data integration, accuracy, and scalability. Overcoming these challenges will require interdisciplinary collaboration, advancements in data processing techniques, and the integration of remote sensing with other agricultural management tools, ultimately enabling implementation of data-driven decision-making that promotes long-term sustainability in agriculture.

1. Introduction

Nature and environment are faced with a number of challenges imposed by anthropogenic activities concerning food, feed, and energy production (Gliessman et al., 2022). As these pressures intensify alongside growing resource demands and technological advancements, the concept of agricultural sustainability becomes central to maintaining productive, profitable, and resilient farming systems that protect natural resources and ecosystem integrity. While agricultural sustainability covers a wide spectrum of concerns and perspectives, the main task is to balance current food and resource needs without degrading the environmental, social and economic building blocks that support future agricultural activities (FAO, 2014). At its core it means producing food and materials in ways that preserve soil, water, and biodiversity; minimize pollution and greenhouse gas emissions; use nutrients and other inputs efficiently; support the livelihoods of farming communities and contribute to social well-being; while also remaining resilient to climate impacts, market demands, and other environmental stressors (Robinson, 2024).

Among the many dimensions of agricultural sustainability, nutrient management can be considered a particularly fundamental issue in part because it directly affects many aspects of the functioning of agroecosystems, including ecosystem health, soil quality, and agricultural productivity (FAO, 2025). Inefficient application strategies, both in terms of quantity and timing, often result in vast amounts of unabsorbed nutrients escaping into the atmosphere, groundwater cycle or in surface water flows (Roland II et al., 2022). The loss of nutrients from productive land effectually depletes the nutrient pools available to the intended crops, and when coupled with high-intensity agricultural practices that lack conservation efforts, it can initiate multiple pollution pathways with various cascading environmental impacts and severely degrade topsoil health and productivity (IPCC, 2019).

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Although the mismanagement of nutrients at field-level has detrimental effects on surrounding environments, the way land is organized and planned across larger spatial scales also plays a critical role in shaping environmental conditions. Effective protection of natural environments therefore requires both reducing nutrient spillover into surrounding ecosystems and thoughtfully planning landscapes with ecological conservation in mind. Global land use and land cover (LULC) trends show a shift toward expanded infrastructure and increased cropland at the expense of deforestation, a pattern that has driven the loss of biodiversity to a state of crisis in recent decades (Afuye et al., 2024; Cabernard et al., 2024). Integrating biodiversity conservation principles into LULC planning is crucial for reducing the environmental impacts associated with the growing demand for infrastructure and agricultural land. By guiding new developments with environmental conservation in mind, such as prioritizing the preservation of large continuous natural areas and key biodiversity hotspots, long-term ecological benefits can be achieved, supported by restoration strategies like rewilding (Svenning et al., 2024).

While the protection of natural environments brings many benefits, including resilient ecosystems, biodiversity protection, reduced climate impacts, and positive feedback to crop production, agricultural sustainability must also maintain food production levels to meet societal demands (Tilman et al., 2011; Tscharntke et al., 2012). Meeting the growing need for food, feed, and energy therefore requires a balanced and strategic agricultural management plan to ensure food security. A viable approach includes large-scale planning, prioritization, and restructuring of LULC, combined with the sustainable intensification of existing agricultural areas, to secure resources while preserving natural environments (Thomson et al., 2019). Addressing nutrient pollution, its associated environmental impacts, and ongoing LULC change through a holistic land management plan is thus essential for achieving a sustainable balance between agricultural productivity and environmental integrity.

One approach that has recently gained prominence for assessing agricultural sustainability through an ecosystem-based perspective is the framework of Nature-based Solutions (NbS), which links to a number of different definitions, each emphasizing varying criteria (Sowińska-Świerkosz and García, 2022). One of these definitions from IUCN is "actions to protect, sustainably manage and restore natural or modified ecosystems, which address societal challenges effectively and adaptively, while simultaneously providing human well-being and biodiversity benefits" (Cohen-Shacham et al., 2016). This definition describes a concept similar to pursuing an ecosystem-based approach in agricultural management and will be the focal definition used in this review. This implementation of NbS in managed agricultural ecosystems is the idea that embraces solutions promoting a balanced ecosystem and relying on ecosystem services to mitigate sustainability challenges while still maintaining production levels (Millennium ecosystem assessment, 2005).

One practical example of how NbS can be implemented in agricultural systems is the incorporation of grassland into crop rotations. By inserting more grassland into a cropping rotation system, reaped benefits include higher water retention, nutrient extraction, and avoidance of bare fallowing where soil erosion and albedo effects could interfere (Blanco-Canqui and Wortmann, 2017; Liu et al., 2022). These benefits can be understood as ecosystem services provided by the presence of grass, compared to leaving the field as bare fallow or planting crops that cannot effectively utilize the remaining soil nutrients. From a NbS perspective, the sustainability benefits of grassland implementation can be further enhanced when integrated into a circular production model at landscape scale. Optimal planning that considers factors such as farm type, previous crops, and proximity to biogas facilities or biorefineries, can help ensure the appropriate quantity and strategic placement of grassland to maximize both environmental and economic benefits (Ding et al., 2024).

To monitor and evaluate the effectiveness of NbS implementations or other sustainability approaches, remote sensing (RS) offers a powerful and scalable monitoring tool for assessing environmental responses and management impacts across agricultural landscapes (Kumar et al., 2021; Miller et al., 2024). Using RS technologies can offer critical insights into land use changes, ecosystem health, and the overall sustainability of agricultural practices. For more than a decade, advancements in RS data sources have led to a significant increase in studies investigating the potential of these data sources to solve time consuming, labor-intensive, and expensive methods of agricultural management and monitoring (Shea et al., 2022; Zhang et al., 2022). Several recent studies have provided comprehensive overviews of how RS can be applied in agriculture, highlighting the types of data that can be extracted and translated into agroecological insights through modeling or empirical relationships (Ahmed et al., 2024; Begue et al., 2018; Weiss et al., 2020). These studies offer valuable perspectives on the broad applicability of RS technologies, detailing the potential of various data types and their relevance in agricultural contexts. Most of these studies focus mainly on improving the method of integrating these data sources without revealing intentions of changing the status quo of agricultural practices (Weiss et al., 2020).

Contrarily, the aim of this review is to explore a wide selection of current satellite RS applications used in agricultural contexts and demonstrate how these methods can instead be utilized in the transition towards more sustainable management strategies. Our target contribution is to highlight representative examples of each identified RS application and examine the sustainability potential, rather than to provide an exhaustive compilation of studies on the topic of RS applications in agriculture. The scope has been focused specifically on studies that utilize RS data from satellite sources, excluding studies that primarily rely on aerial and proximal RS data. The reason for this restriction is to avoid a heavy preference for studies in precision agriculture, a topic that has already been thoroughly investigated and frequently incorporates both aerial and proximal sensors (Sishodia et al., 2020). Based on the compilation of RS applications, we elected three key concerns in sustainable agricultural management to focus our discussion on: nutrient management, environmental impact of agricultural production, and maintaining food security. Although many of the applications discussed are not explicitly designed to ensure sustainability but instead focused on utilizing RS data to optimize production efficiency and value, we examined their potential for repurposing within sustainability-aligned contexts.

The first section outlines the method used to extract and select the content papers. The subsequent sections present and discuss applications of remote sensing techniques in agriculture, focusing on the three identified key areas of concern. Following this, we propose future research directions aimed at exploring new possibilities for utilizing these methods. This section also highlights some of the key challenges and limitations in RS that require further attention in future studies. Finally, the review is concluded with a recap of recurring themes identified in the discussion.

2. Methodology

2.1. Search strategy for content papers

This review has been shaped by the guidelines provided by the Preferred Reporting Items for Systematic Reviews and Meta-Analyses, i.e. the PRISMA 2000 framework (Page et al., 2021), to ensure replicability and a transparent search and selection strategy. The literature search was performed using two of the largest interdisciplinary bibliographic databases of peer-reviewed academic literature, Web of Science (WoS) and Scopus, which together provide broad and reliable coverage for this topic. The scope of this review focuses specifically on satellite-based RS applications relevant to conventional, large-scale agricultural systems, ensuring that the discussion reflects the field scales and technological context typical of contemporary agricultural production. Initial searches were performed on a combination of different keywords, and their derivatives, to get a sense of the amount of literature available in different scenarios. The selected keywords were categorized into four different topics relating to management parameters (bio-based fertilizer, crop rotation, green biorefinery, nature-based solution, and nutrient management), data type (multisource data, remote sensing, satellite imaging, and sentinel), general research field (agriculture and crops), and a fourth topic of irrelevance (aquatic, marine, city, buildings, roof, wall, urban, grey, natural disaster, and natural hazards) to exclude unwanted topics. The first three topics were combined using the Boolean operator AND to ensure the search was targeted within the multifaceted scope of this review. The fourth topic was connected using the Boolean operator NOT to signify which avenues were not relevant for the scope. The actual search was performed and extracted using the combination of keywords as emphasized in the appendix (A1). The records from each database (WoS n = 490; Scopus n = 753) were filtered to include papers written in English and imported into a web-based review management software, Covidence (Covidence, n.d.). The software removed duplicates (n = 565) and prepared a final collective dataset (n = 678) for the screening processes.

2.2. Selection strategy for content papers

The first round of screening (n = 678) viewed titles and abstracts and selected records suitable for the scope of this review (Fig. 1). Records included in the first screening round met the criteria for describing applications of spaceborne RS data, in combination with other data sources, within the context of agricultural management, nutrient management, or agricultural landscape planning. Records excluded in the first screening round were primarily focused on applications of RS data from airborne or proximal sensors – which are out of scope for this review. Other exclusion criteria consisted of records where satellite RS data was only utilized to validate results, where the context was outside of the agroecological scope, where the paper intended to solve environmental issues less related to agricultural practices, where the degree of novelty was insufficient to distinguish methods or if the record was a published conference paper or similar instance.

The second round of screening (n = 121) viewed full-length papers and selected the records to be included and evaluated more comprehensively. This screening categorized the records into groups corresponding to the identified key concerns of nutrient management (including soil degradation and water pollution), environmental impacts of agricultural production (such as climate pressures, deforestation, and biodiversity loss), and considerations related to food security. Within

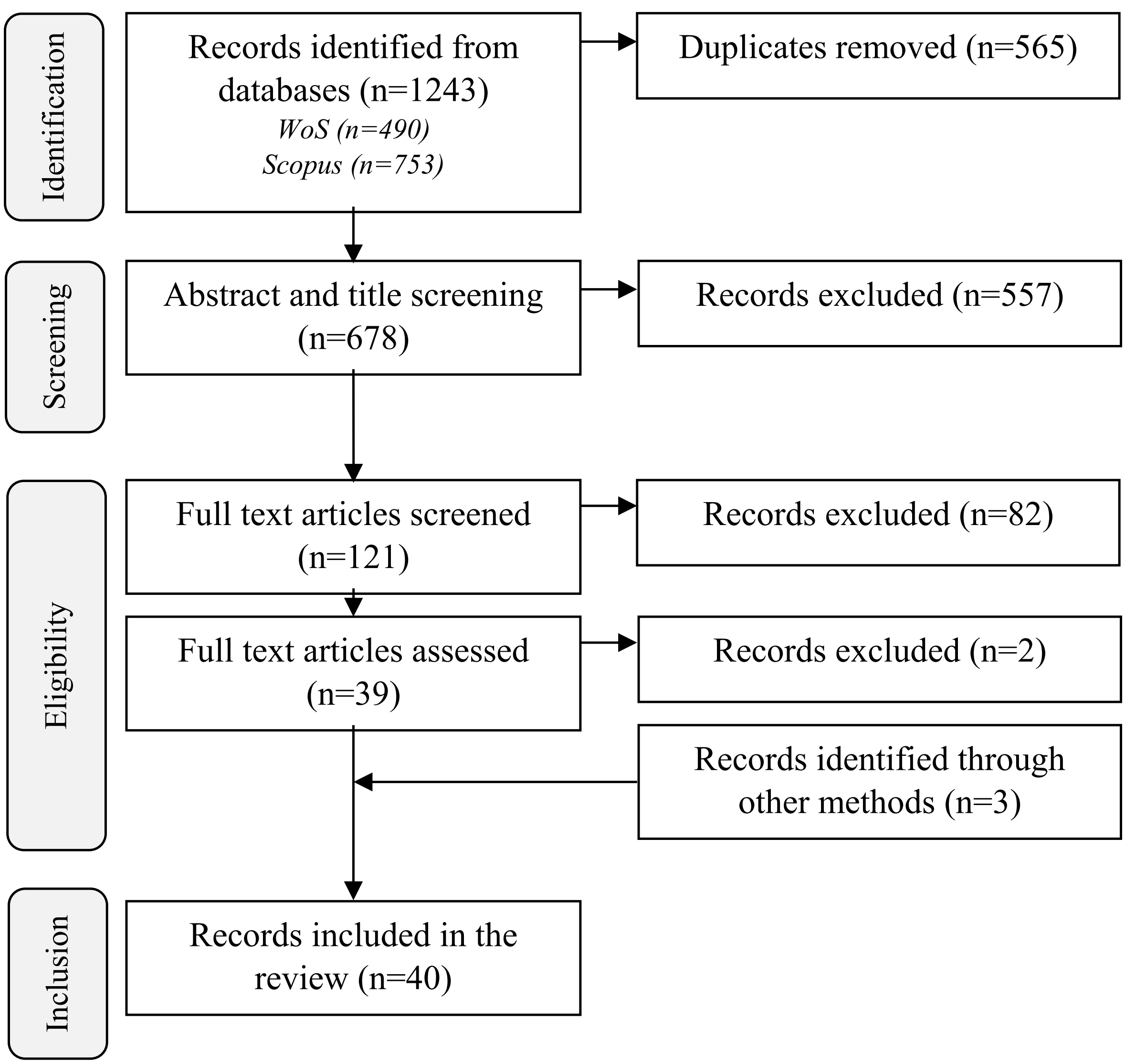

Fig. 1. PRISMA flow diagram depicting the selection strategy and the screening process resulting in the final dataset of included records.

each group, the most relevant records were selected for further evaluation (n = 39). The selection prioritized records describing novel applications of satellite RS data in large-scale farming systems and excluded records that pertain to small-scale farming, records not contributing with new conceptions of existing datasets nor describing new methodologies.

During the final evaluation of the selected papers, a few papers were excluded (n = 2) because closer examination revealed that they did not contribute new or relevant insights to the scope of this review. In addition, other relevant content papers were identified and included (n = 3) through expert consultation, where domain specialists recommended relevant studies not captured by the initial search. These papers were assessed against the inclusion criteria and subsequently incorporated. The final selection of content papers (n = 40) can be found listed in the appendix (A2). The following sections synthesize and discuss the applications of remote sensing techniques in agriculture across the three identified areas of concern.

3. Sustainably managing nutrients

From a crop production perspective, the management of nutrients encompasses nearly all activities undertaken by farmers in their fields prior to a harvest event, as these strategies ultimately serve to direct nutrients into their production for optimal growth, achieving higher economic yields. Effective nutrient management therefore plays a central role in both sustaining productivity and minimizing environmental losses. This section focuses on management practices aimed at improving soil quality and preserving nutrients in the soil, to avoid unabsorbed nutrients leaching or otherwise escaping the intended crops, while maintaining or improving economic yield.

3.1. Soil management practices and their impact on soil condition

Neglecting to account for sustainability in nutrient management decisions can lead to a gradual decrease in soil quality, reducing the availability of nutrients for subsequent crops (FAO, 2015; Vitousek et al., 2009). Practices such as monocropping, bare fallowing, and intensive tillage regimes have been shown to accelerate soil degradation and diminish its productive capacity (Begue et al., 2018). Conversely, minimizing tilling, implementing crop rotation, raising crop diversity (including intercropping, diversity in crop rotation schemes, and genetic diversity), and covering bare fallowed fields with residue, grass fallow, catch, or cover crops can contribute to improved or maintained soil quality (Ahmed et al., 2024; Sharpley et al., 2015). In particular, one of these key soil improvement management practices, crop rotation, has a long list of co-benefits, including control of pests, diseases, and weeds in the fields, and reducing the need for pesticides. Furthermore, crop rotation promotes long-term management of excess nutrients, leading to decreased fertilizer dependency and improved soil properties mainly due to the preservation of nutrients in the soil (Begue et al., 2018; Mueller-Warrant et al., 2011). Introducing crop rotation with multiple crops distributed across different fields within the same farm in a given year can effectively reduce nutrient losses, enhance soil organic matter (SOM), and improve water retention properties, all while providing a higher per crop yield (Begue et al., 2018). It is also possible for more than one type of crop (e.g., combinations of main crops, pre-crops, and/or cover crops) to be grown in the same field within a single year. From a regional point of view, it would be beneficial to know where and which crop rotation patterns are being implemented in farming areas.

Monitoring and detecting crop rotational patterns using models rooted in RS data is a viable approach and requires a set of criteria to be fulfilled or considered. These criteria consist of incorporating a multi-annual temporal scale, a satellite source enabling an intra-annual sampling scheme representative of a growing season, i.e. high revisiting frequency, and a suitable spatial scale for capturing study site variability, i.e. high resolution (Song et al., 2021; Wang et al., 2023). One such example is presented in Mueller-Warrant et al. (2011) where they extract crop rotations based on a crop classification model on a time series of satellite images (30 m resolution) from Landsat 5 TM, Landsat 7 ETM+ and Moderate Resolution Imaging Spectroradiometer (MODIS), which was twice resampled to a 30 m resolution for compatibility with Landsat data. Field disturbances, such as mowing or harvest, can have a major impact on classification, and it is thus important to consider the satellite revisiting time and whether to include an intra-annual multi-temporal scale. Additionally, the selection of an appropriate resolution accounting for study-site field sizes is important to avoid a mixing effect where fields might be grouped (Mueller-Warrant et al., 2011; Pinto et al., 2017). Contemplating the technical properties of the satellite dataset is one of the most important duties prior to a task involving RS data. In Mueller-Warrant et al. (2011), they chose multiple sensors, high-resolution images, and a multitemporal dataset to get a comprehensive digitalized account of the study-site growing seasons and for extracting crop rotation patterns.

Though crop rotation unquestionably generates a large array of benefits, why then is it not more widespread on a global scale? In some places, like parts of Europe, crop rotation is already standard procedure. In the Common Agricultural Policy (CAP) reform of 2013, the European Union adopted a financial strategy beneficial for agricultural management respecting and complying with a set of practices advantageous for climate and environment, the Greening requirements (European Commission, 2013). In Denmark, these Greening requirements about the inclusion of permanent grassland and cultivation of multiple crops have been implemented in national policies, and the effects monitored since (DCA – Nationalt Center for Fødevarer og Jordbrug, 2022). However, that is not the global story. In other regions, management strategies are mainly left completely up to the farmer, often needing to prioritize short-term economic gains, resulting in little to no crop rotation or very simplistic rotations. In these cases, the adoption of a particular NbS or other sustainable strategy would require incentives – either direct economic benefits or broad environmental benefits that translate into financial support for the farmer – to make it a viable and long-term choice. Focusing on the economic incentive perspective, Peltonen-Sainio et al. (2019) use RS data to estimate pre-crop values (a measure to identify how beneficial different previous crops are for a subsequent crop in rotation) to promote crop rotation as an economically beneficial strategy. It has further been established that the implementation of suitable pre-crops can improve both water accumulation available for the subsequent crop as well as the productivity of that crop (Pichura et al., 2024). Manual methods of determining pre-crop values require extensive experiments that are expensive in both equipment and labor. Therefore, using RS data to estimate these values will automate the process, optimally creating a dynamic and transferable method that includes many crop types and can easily provide pre-crop values at a lower cost for long-term utility of the results. There are of course limitations to these pre-crop value estimations such as using normalized difference vegetation index (NDVI) as an estimation for yield rather than actual yield values (which is a sparse datatype) and the incapability of factoring for management strategy, however, it remains an excellent argument for implementation of crop rotation (Peltonen-Sainio et al., 2019; Pichura et al., 2024).

Conventional tillage practices have unfavorable effects on soil organic carbon (SOC), soil nutrient leaching, water retention capabilities and susceptibility to erosion while the benefits of switching to a lesser tilling regime can ultimately lead to a reduced need for additional nutrient supply (Begue et al., 2018; Hagen et al., 2020). When combining reduced- or no-till practices with other sustainable management strategies, the derived effects on soil condition can lead to desirable effects such as higher nutrient use efficiency and lower leaching rates (Ahmed et al., 2024). Therefore, knowledge of tilling occurrences would be a valuable indication of soil status. When using RS data to monitor tilling events or map tilled and untilled fields, it is essential to have either precise timing of image acquisition or continuous temporal coverage to ensure that signs of tillage are captured in the dataset (Begue et al., 2018; Mueller-Warrant et al., 2011). Different types of sensors can be used to capture the modified state characteristic of tilled systems, for instance, the presence of crop residues or the structural surface of the field. Optical sensors excel at till detection based on the reflectivity of the left-over crop residues on non-tilled fields whereas synthetic aperture radar (SAR) sensors are capable of determining a difference in surface roughness of tilled and non-tilled fields (Begue et al., 2018). These two approaches both serve to indicate if, and by extension also where and to some degree when, tilling events have occurred, assuming that the collected satellite time series overlaps with the timing of the tilling event.

Conservation tillage fields (reduced- or no-till fields) can also be obtained from the Operational Tillage Information System (OpTIS), which is a software tool that uses RS data to map trends in tillage, cover crops, and crop rotation. A study using OpTIS and RS data extracted from multiple sensors on MODIS, Landsat, and Sentinel-2 to map conservational tilling practices, was able to assess the impact of tilling on carbon and N dynamics in agroecological systems (Hagen et al., 2020). They were able to identify tilled fields and provide insight into the SOC status of the study area. The status of SOC is important knowledge in climate hange mitigation, as it reflects the amount of carbon stored in the soil, which helps maintain soil health, prevent erosion, and preserve soil moisture (Hagen et al., 2020; FAO, 2015). An alternative approach to estimating SOC status using RS data involves calculating spectral indices (SIs) or topographic indicators and validating them against measured SOM values. SI indicative of SOC can be calculated from the spectral bands of RS data, where it has been observed that the precision improves when using multitemporal data (Minhoni et al., 2021). Further improvements in accuracy can be achieved by utilizing hyperspectral RS data to detect non-photosynthetic vegetation, including crop residues, plant litter, and standing dead or dying vegetation (Pepe et al., 2022). Although hyperspectral data is superior in determining the presence of non-photosynthetic vegetation, the long revisiting time of the satellites containing hyperspectral sensors complicates the establishment of real-time monitoring schemes. This creates a trade-off scenario between higher accuracy of estimations over more frequent observations for continuous monitoring.

Other applications of RS-based SI estimations include the mapping of bare fallowed areas, which can serve as optimal locations for the implementation of conservation strategies such as sowing cover or catch crops. Pinto et al. (2017), while focused on characterizing seasonal fallows rather than conservation planning, used a time series of MODIS images (250 m resolution) to calculate NDVI and identify summer and winter fallow areas. They used moderate resolution images, which could indicate what sub-regions contained certain proportions of summer and winter fallows (Pinto et al., 2017). However, using a higher resolution can be used to map bare fallowing on a field level (Liu et al., 2022). Conversely, RS can also be used for mapping established cover crop fields in much the same way, by calculating NDVI based on satellite bands (Fan et al., 2020). This study estimates cover crop sowing dates based on Sentinel-2 observations, which are then used in combination with cover crop productivity to determine what the optimal sowing date of cover crops would be for the studied region (Fan et al., 2020). This particular RS application and way of thinking could serve as a valuable monitoring framework, ensuring that climate policies remain effective and adaptable in a dynamic climate scenario, rather than becoming barriers to compliance. RS data already provides a range of well-established applications, including the ability to estimate crop rotation patterns, tilling events, SOC status, and the mapping of bare fallowed fields across various spatial and temporal scales. When applied strategically, these tools can move beyond descriptive monitoring to actively support more sustainable land management decisions. Integrating these RS-based approaches into agricultural planning can help optimize farm management, reduce environmental impacts, and promote long-term sustainability goals within crop production systems.

3.2. Monitoring nitrogen dynamics and water-related pollution pathways

Application of supplementary nutrients in croplands often produces oversized nutrient pools, resulting in excessive availability of nutrients, particularly N, typically surpassing the N uptake ability of the intended crops, equivalent to lowering the N use efficiency (NUE). This discrepancy in the relationship between N application and N uptake creates a reservoir of unused nutrients that remain in the root zone of the soil for only a relatively short amount of time (not enough time to remain completely available for the following crop) before it leaches to water systems or is emitted to the atmosphere as greenhouse gas (GHG) or other N compounds (e.g. N_2). The pollution of excess N into water systems via runoff and leaching is the lead cause of reduced drinking water quality, eutrophication events, algae blooms, hypoxia and the resulting loss of biodiversity in natural aquatic environments. Actions to diminish water pollution from nearby cultivated areas are centered around conservation strategies optimizing fertilizer usage, keeping the nutrients in the soil, or removing excess nutrients via biological processes. While the ideal nutrient management scenario is a closed-loop system where the application rate precisely matches the rate of uptake, it remains largely unrealistic. However, the advancements in precision farming systems are working towards closing that gap (Victor et al., 2024). Sishodia et al. (2020) and Victor et al. (2024) both provide an excellent overview of the applications of RS data within the scope of precision agriculture. A central concept of precision agriculture involves equipping machinery with AI-driven systems that utilize sensor outputs and vegetation indices to estimate nutrient status. This enables real-time assessment of a field's nutrient deficiencies and facilitates the application of fertilizers based on actual requirements (Sishodia et al., 2020). Advantages of this management strategy include lowering the leaching rates and other pollution pathway rates, resulting in a reduced need for purchasing synthetic fertilizer. However, one of the main disadvantages of precision agriculture is the cost of the advanced machinery required, which makes it unfeasible for some farmers.

The acquisition of precise N status and N requirements is not exclusive to precision farming technologies, which frequently rely on airborne or proximal remote sensors. A comparative study investigating various vegetation indices (VIs) and utilizing data from proximal, airborne, and spaceborne sensors demonstrated that spaceborne RS data could reliably predict N status. Furthermore, the study showed that N requirement calculations based on this data closely aligned with field observations. For spaceborne observations, Sentinel-2 data was used to reveal that plant N uptake could be effectively estimated using mean reflectance values (Peng et al., 2021). Another study compared various modeling methods, satellite sources, and nutrient types to uncover that foliar nutrient quantity could be obtained from satellite-derived features, such as VIs, texture features, and spectral reflectance (Huang et al., 2024). This suggests that retrieving nutrient status from satellite sources is an available alternative to precision agriculture methods. If this field-level RS knowledge could be made accessible to farmers, perhaps general nutrient application strategies could follow N requirement rates rather than maximum N allowance rates. These methodologies described are closely linked to estimating nutrient application requirements, and a related task would involve monitoring the actual application. RS data can already be utilized to monitor some types of nutrient applications, for example by tracking liquid manure application through irrigation systems (Shea et al., 2022). Liquid manure application often results in nutrient runoff and leaching into water systems. Identifying these application events could support land planning strategies, particularly for areas that involve the circular process of manure collection, storage, and subsequent field application for feed crop production. For these particular systems, information on the application events could be an important first step towards optimal and circular utilization of manure fertilizer to avoid overapplication or storage of surplus manure supply.

Following the N cycle, monitoring the flow of water from fields to nearby water systems is a critical step in the pollution pathway. With RS data from Sentinel-3, it is possible to calculate the Forel-Ule Index, used as an indicator for water color variability, to help determine the extent of different river plumes in a time series of data (Heal et al., 2023). This can assist in identifying the sources of dissolved inorganic N, enabling targeted conservation efforts in prioritized catchment areas. Incorporating high-loss areas into the planning of conservation strategies provides an effective starting point for mitigation efforts. An alternative approach for identifying high-loss catchment areas is to map and use cyanobacteria blooms as an indicator of nutrient overload. With Medium Resolution Imaging Spectrometer (MERIS) and Agency Environment Satellite (ENVISAT) data, Marion et al. (2017) detected the presence of phycocyanin pigmentation, which is indicative of cyanobacteria bloom levels (260 m × 290 m resolution). These recordings of cyanobacteria blooms were positively correlated with the proportion of cultivated areas near open water sources, confirming that bloom levels are higher in areas with a high potential for N loss (Marion et al., 2017). Using RS data to detect blooms could similarly be used to map critical areas of high-loss potential for prioritizing conservation efforts.

Continuing to examine water flow from fields, tracking and mapping irrigation can help identify high-loss potential, particularly when irrigation coincides with nitrogen application timing. This is a well-studied topic within water flow monitoring, where costly and extensive field sample collections and very high-resolution RS data are typically involved (Begue et al., 2018). Since shortwave infrared (SWIR) satellite bands are closely related to soil moisture, it can be used to detect irrigation features. Gokkaya et al. (2017) used SWIR from Landsat 8 to look at land areas before and after heavy rainfall events and illustrated that it is possible to detect which areas are tile-drained and thus dry off at a quicker pace. These tile-drained systems are problematic, because though they are designed to drain permanently wet soils and hence make them suitable for agriculture, they also serve as a direct pollution pathway into nearby water systems (Gokkaya et al., 2017). An alternative method for predicting tile drainage involves applying a machine learning model that combines RS satellite data with environmental factors such as surface temperature, soil characteristics, and weather conditions (Wan et al., 2024). Having an overview of the location of these historically implemented drainage systems would help in sustainable land use planning to avoid placing nutrient-dense cultivation on those soils.

4. Considering environmental impacts of agricultural production

Agricultural management practices play a key role in shaping both climate dynamics and environmental integrity. Many aspects of climate trends driven by human activities can be monitored and analyzed with multisource data that includes RS sources, to provide valuable tools to assess changes in land use, vegetation, and atmospheric conditions. Understanding these dynamics is essential for identifying the sources of pollution and GHG emissions, evaluating land degradation and deforestation, and developing strategies that integrate climate change mitigation with biodiversity conservation.

4.1. Climate change mitigation actions

On a global level, climate change is closely linked to intensive agricultural production, as the sector is a significant contributor to greenhouse gas (GHG) emissions, particularly nitrogen dioxide (N_2O), and also contributes largely to other forms of pollution (IPCC, 2019). Indirectly, these other types of pollution can lead to additional increases in GHG emissions, for example when nitrites and other N-compounds are oxidized in the so-called N-cascade, inducing risks of further N_2O emissions (Sutton et al., 2011). Climate solutions in agriculture primarily aim at either reducing GHG emissions, which represent the most climate-relevant form of N loss due to their high global warming potential, or to enhance carbon sequestration, thereby increasing the capture and storage of atmospheric carbon dioxide (CO_2) and achieving net reductions in atmospheric GHG concentrations (Liu et al., 2022; Sun et al., 2020). The reduction of GHGs in the atmosphere contributes directly to a decrease in global warming, as lower atmospheric concentrations reduce the greenhouse effect – the process in which these gases in the atmosphere trap outgoing infrared radiation and warm the Earth's surface (IPCC, 2019). At present, RS technology is not yet highly effective in directly detecting GHG emissions, as many emission processes occur below the spatial or temporal resolution of current satellite sensors (IPCC, 2019). However, RS advancements could potentially facilitate a broader understanding of climate dynamics and support a holistic framework for mitigation in agroecosystems, including monitoring of other climate-relevant parameters, such as surface reflectivity.

Beyond GHG mitigation, the reflectivity of land surfaces also affects global warming. Dark surfaces absorb more heat, while lighter or more reflective ones return more sunlight to space. This reflectivity of sunlight, known as the albedo effect, can therefore contribute to climate mitigation, particularly through the cooling potential of increased reflectivity of certain types of surfaces in agriculture (IPCC, 2019). Liu et al. (2022) explore how changes in management strategies could induce negative radiative forcing and cause a cooling effect from changes in cropland albedo. They investigate the effects of converting from bare fallow areas or seasonally bare fallow areas to cropped areas and from conventional tilling strategies to no-till or reduced-till practices. This study explains how RS data can be used to map bare fallow areas and further make calculations on the reflectiveness of different surfaces. Though surface albedo is readily available from MODIS (250 m or 500 m resolution), Liu et al. (2022) uses Landsat (30 m resolution) band reflectance data to identify fallow areas and calculate surface albedo at higher resolution. This scale selection avoids a mixing effect due to the small field sizes in the study area of the Canadian prairie and facilitates the identification of the spatial distribution of bare fallowed fields. Another similar study identified bare fallowing by using the MODIS surface albedo dataset. Here the intention was to determine if implementation of cover crop strategies would be an effective solution for the whole of South America and precise spatial distribution was of lesser importance (Pinto et al., 2017). The results in Liu et al. (2022) show that both management strategies of converting from conventional tilling to no-till or reduced-till practices and from summer bare fallow to crop had negative local radiative forcing effects. They further concluded that the equivalent atmospheric CO_2 drawdown of the changed albedo is comparable to the potential drawdown caused by carbon sequestration, indicating the significance of evaluating the impact of leaving fields bare (Liu et al., 2022).

The primary objective of converting to no-till practices includes reducing soil disturbance and increasing crop residue left in the field. Linked advantages, beyond the cropland albedo effect benefits, involve lowering the risks of soil erosion and enhancing carbon sequestration (IPCC, 2019). However, albedo effect benefits might have significant potential in mitigation strategies. Ridgwell et al. (2009) used a bio-geoengineering approach for albedo effect benefit research and proposed the adoption of crops having high reflectivity properties. They found that increasing the canopy albedo by 0.04 could lead to a decrease in annual average temperature by 0.11 °C (Ridgwell et al., 2009). Additionally, albedo should be taken into account when using biochar as a carbon enrichment strategy for croplands to mitigate climate change, as the lower albedo of biochar surfaces could potentially offset its carbon benefits (Meyer et al., 2012). From this perspective, could the incorporation of region-specific albedo effects into management strategies or land-use planning be considered a NbS? For example, introducing more green crops to cover the soil, like the mentioned grass-based NbS systems. Implementing crops with higher reflectance, avoiding tillage and fallowing could certainly mitigate warming effects while concurrently increasing carbon sequestration and maintaining soil health.

Another effective application of RS knowledge when considering the effects of a changing climate is leveraging phenological events identified by RS models to adapt and improve classification models (Waldhoff et al., 2017) or to support other agricultural monitoring schemes (Simms et al., 2014). Phenology should be an important factor in agriculture and crop classification since climate change has the potential to alter the timing of land surface phenology (LSP) events such as start-of-season or end-of-season (Machichi et al., 2023). In Simms et al. (2014), VIs calculated or extracted from RS sources were used to identify patterns indicative of LSP events, while also interpreting the underlying significance of various greening peaks. They analyzed NDVI profiles extracted from MODIS (250 m resolution), to see if they mirror LSP events and to explore additional crop information that could be derived from the NDVI profiles. They additionally used survey photographs, reviewed by experts, as reference data to validate primary LSP events in fields, uncovering trends that aligned with the identified LSP events.

The use of RS data from high-resolution satellites for crop classification is most effective when the images are captured during the specific crop's optimal timing for differentiation, which is usually around the flowering stages (Simms et al., 2014). Hence, incorporating phenology models into this process can significantly enhance RS-based crop classification methods. Waldhoff et al. (2017) integrated a phenology model and the resulting acquisition windows for optimal differentiation with a crop classification model. They used a range of satellites for crop mapping and rasterized outputs to a common resolution of 15 m, focusing exclusively on arable land by applying a predefined field mask. The study concluded that the phenology aspect was vital in differentiating between certain crop types (Waldhoff et al., 2017). Amin et al. (2022) likewise used a variation of satellites and created a workflow combining the different datasets to identify key LSP events. They illustrated that utilizing both Landsat 8 and Sentinel-2 data results in better temporal coverage and outperforms phenology models based on singular sensors (Amin et al., 2022).

These studies explore the integration of phenology and emphasize the importance of satellite and resolution selection while addressing several challenges associated with utilizing RS data, including data preprocessing, compilation, atmospheric conditions, and satellite revisit times. Mapping the phenology of crops and determining the potential shift could be incorporated into agricultural management to optimize the timing of sowing and harvesting events. Furthermore, phenological events could be utilized in crop classification models to indicate the optimal timing of data collection, optimizing the precision of the models. This knowledge of timing is especially important for some crops where differentiation is most precise in the short flowering period, as with the poppy, where the classification model is quite sensitive to a potential shift in phenology (Simms et al., 2014). This climate change-induced shift in the critical stages or the length of the growing season can be obtained from RS data and can be valuable for sustainable agricultural management strategies.

4.2. Deforestation and terrestrial biodiversity

Destruction, fragmentation, or deterioration of habitats is undeniably the biggest challenge for species survival and the primary driver of biodiversity loss. From a global perspective, deforestation is often viewed as a necessary means to satisfy the basic needs of the increasing human population. Urbanization and resource utilization typically require more space and resources, and more than what is available to be sustainable long-term. The important question is then, is there a more biodiversity respectable way to attain food security while still protecting natural habitats? One approach to balancing agricultural production and environmental conservation is to increase the intensity of existing cropland rather than expanding agricultural areas (Estel et al., 2016). When expansion is necessary, it should be carefully planned and guided by land use and land cover (LULC) considerations, following the land sparing principles. This concept prioritizes the protection of larger, connected natural areas with high ecological value, while concentrating urban development and agricultural expansion in less sensitive regions. In contrast, the land sharing approach promotes less intensive, mixed-use landscapes that integrate wildlife-friendly farming practices to support both biodiversity conservation and agricultural production.

Regardless of the approach, understanding and monitoring how land use changes over time is essential for evaluating their outcomes. Mapping changes in LULC is therefore important for land-use planning, monitoring climate change and biodiversity, ensuring food security (Verburg et al., 2013; Zelaya et al., 2016), and predicting future impacts of provisioning ecosystem services (Kandziora et al., 2014). A well-established application of RS data is to map and classify LULC and by using satellite images from multiple years it is possible to detect the gradual changes in LULC (Kandziora et al., 2014; Zelaya et al., 2016). In Kandziora et al. (2014) they used multiple Landsat images from 1987 to 89 and from 2007 to 11 to generate LULC maps classified into 9 categories to evaluate the change over time, the impacts on ecosystem services and to detect crop rotation patterns. Zelaya et al. (2016) used a time series from each year to identify both summer and winter crops and used 8 pre-defined classifications to produce LULC maps from 1999 to 2013. It is important to note that LULC maps based on RS data by default produce pixel-based analysis. Converting classification units to farms or fields in object-based analysis (OBIA) can help get a better classification (Ahmed et al., 2024), avoiding the mixed pixel and edge effects, and create a better connection with the actual context behind the classification (Zelaya et al., 2016). Ultimately, RS-driven LULC mapping provides a powerful means of monitoring land changes, guiding conservation strategies, and supporting sustainable agricultural intensification while minimizing biodiversity loss and climate impacts.

5. Ensuring food security

The global challenges associated with agricultural practices, particularly in managing nutrients and making environmentally conscious decisions, significantly impact both natural and modified environments, calling for cautious and restrictive measures. In contrast, ensuring a reliable food supply for the growing global population often demands intensification or expansion of agricultural activities. The key objective, therefore, is to strike a balance that addresses both sustainability and productivity. As ecosystem engineers, we must adapt to these challenges by considering and aligning both human and environmental needs in our strategies and actions.

Cropland expansion and some aspects of intensification, such as increasing applied nutrient rates and soil disturbances, would generally dissatisfy the aim of diminishing environmental challenges. However, accomplishing a large-scale restructuring of agroecosystems and supply chains could fulfill both targets of ecosystem stability and food security. Some sort of expansion or intensification of underperforming croplands is necessary for increasing food demands, though this should be planned on a larger landscape scale to attain the lowest possible regional environmental impact (Estel et al., 2016). Maintaining larger areas of connected natural habitats with a focus on preserving prime biodiversity hot spots has direct positive impacts on especially local biodiversity, climate mitigation, and local pollution effects (IPCC, 2019). To minimize the need for expansion, identifying underperforming cropland with potential for intensification and enhanced productivity is essential, often requiring the use of LULC maps. For instance, satellite-derived NDVI, crop masks, farm economy data, and switchgrass potential were utilized to locate underperforming farms that could achieve greater economic benefits by cultivating switchgrass for biofuel facilities instead of their existing crops (Gu and Wylie, 2017). This exemplifies the type of transformation necessary to optimize cropland use at a landscape scale, moving beyond the prevailing focus on farmer-centric optimization. Similarly, Estel et al. (2016) utilized MODIS data and NDVI calculations to identify inactive cropland and assess performance and intensity dynamics, which are critical insights for sustainable LULC planning.

Assessing change in LULC over time is important to evaluate the effects of change and understand the current land compositions. Multiple studies have aimed for this type of LULC mapping by using a time series of Landsat images (30 m resolution) and even included some degree of crop differentiation within the LULC categories (Kandziora et al., 2014; Zelaya et al., 2016). Kandziora et al. (2014) monitored landscape changes between 1987 and 2011 and were able to provide clarity on some of the observed crop rotation patterns. These maps are highly valuable as they validate the trend of cropland expansion. A similar approach to LULC maps was performed by Simms et al. (2014) to collect a more complete understanding of the agricultural structure in Afghanistan by determining and forecasting crop development cycles, investigating water availability, and predicting disease influences on crop production.

A key aspect of LULC mapping is identifying the crop types and detecting crop rotation patterns through consecutive years of RS data. This information on crop type distribution is particularly beneficial in LULC planning, for example, in scenarios where local feed production for livestock is prioritized, and crop quantities have to effectively align with livestock numbers. Crop types in LULC mapping are often aggregated into broad categories, such as grassland, cereals, legumes, or vegetables, or grouped entirely as cropland. This aggregation of crop types helps to simplify the modeling, especially when certain crops are underrepresented or when backing data is insufficient. Waldner et al. (2019) addressed the challenge posed by rare and infrequent crops, which can reduce the accuracy of crop classification models. They quantified the effects of crop type imbalance on model performance and proposed a method to balance datasets by removing or generating synthetic data for minority crop classes, ultimately boosting classification accuracy. (Waldner et al., 2019). Similar unsolved challenges arise when mapping land uses that are not monocropping and not easily distinguishable, such as identifying intercropping fields, strip cropping, or agroforestry.

Crop classification in itself is a huge topic and has been vastly studied from various approaches in the last decade (Machichi et al., 2023; Weiss et al., 2020). Crop classification models are generally more accurate when including multitemporal data series, especially when focused on diverse crop compositions with varied phenological timing or when differentiation between crops peaks at distinct phenological events (Kussul et al., 2018; Zhang et al., 2022). Furthermore, the inclusion of multiple years in a time series of data will expose both intra and interannual patterns and make a more robust classification model (Quinton and Landrieu, 2021). Recent advancements, particularly with the availability of Sentinel-2 data, offering a revisiting time of five days, have enabled the detection of temporal phenology patterns and achieved high-accuracy crop classification models, with some studies reporting accuracy rates as high as 97.5 % (Quinton and Landrieu, 2021). Waldhoff et al. (2017) applied a phenology model to identify the optimal windows for crop differentiation and used these periods to enhance crop classification. Similarly, Zhang et al. (2022) demonstrated that their model's classification accuracy, ranging between 80 % and 90 %, improves as the growing season progresses, given that some crops are more recognizable in the blooming stage. Their approach involved combining historical RS data with known crop type observations to create a robust crop classification model, which was subsequently applied to in-season RS data for real-time crop classification (Zhang et al., 2022). This integration of phenological knowledge with time series RS data has proven effective in improving classification reliability and precision.

Another step to further advance crop classification models could involve adopting a multimodal approach. Using SAR data, rather than optical satellite data, is a more reliable type of RS data to obtain from cloud-prone regions. Furthermore, like optical satellite RS data, SAR data can detect crop rotations from long-term crop type monitoring programs without considering disturbances caused by weather or cloud cover (Zhou et al., 2022). Multitemporal SAR data collection can produce phenological backscatter curves that can be utilized as crop classification features. Backscatter variations in multitemporal SAR data are composed of changes in crop canopy, crop structure, and soil physical parameters, which help users discriminate various crop types (Zhou et al., 2022). SAR data can potentially be used to replace optical RS data in periods of high cloud cover to get a more complete time series (Kussul et al., 2018; Machichi et al., 2023). Synergistically fusing RS data sources with complementary strengths, such as the high spatial resolution of optical sensors and the weather-independent capabilities of SAR data can provide a more comprehensive and reliable representation of crop conditions and phenological patterns (Blickensdörfer et al., 2022). Using a multimodal RS data approach (radar and optical) could be key for mitigating data gaps in optical crop type prediction (Giordano et al., 2020). Limitations of the multimodal approach include the coarser resolution of SAR data, which makes it less effective at capturing variations caused by smaller field sizes. Additionally, SAR demonstrates a high success rate in crop classification, but this is often limited to specific crops, reducing its general applicability in diverse agricultural landscapes (Giordano et al., 2020). An alternative synergy solution for a data gap issue when using optical RS data, could be the inclusion of multiple optical sensors (Waldhoff et al., 2017). Even though the process of combining these different types of resolutions, revisiting times and orbital paths can be a difficult task, utilizing synergies in RS data can typically enhance the robustness and accuracy of crop classification or LULC models.

While knowing the location and composition of cropland and other land types through LULC modeling is essential, effective planning of crop distribution must also incorporate biomass information to ensure the sustainable utilization of already productive land. Prediction of actual yield is monumentally difficult to attain without manually weighing each harvested field, and even then, procedures and equipment are not fully operational. Harvesting machines with incorporated weighing techniques are costly to acquire and maintain, they require frequent calibration, and they are more complex to operate and to integrate with other farm management software (Rose and Chilvers, 2018). Moreover, measurement uncertainties can arise due to specific crop characteristics, variability in terrain, and environmental conditions during data recording (Mulla, 2013). Therefore, RS-based approaches for yield estimation often utilize NDVI or other VIs as biomass indicators (Moriondo et al., 2007; Peng et al., 2021). However, as NDVI captures a momentary measure of greenness, it is only indirectly linked to yield requiring the inclusion of several other factors. NDVI is more effective for assessing plant health and could be used in near-real-time agricultural monitoring to predict biomass and evaluate crop conditions. This enables timely problem-solving and helps maximize economic yield if used for current-season management decisions solving problems such as plant diseases, and nutrient or water stress. Such a replicable and transferable framework has been designed to process current-season RS data, enabling the generation of in-season crop maps (Zhang et al., 2022). Although NDVI alone does not directly correlate with yield, these early-season crop maps derived from NDVI serve as essential input for crop models used in crop production forecasting (Kussul et al., 2018).

An alternative to traditional NDVI-based approaches for estimating crop yield is the application of machine learning models that predict yield by integrating historical yield maps or other types of yield reference datasets with remote sensing inputs. This typically involves training a yield prediction model using historical yield maps combined with RS data and applying time-integrated calculations across a growing season (Lai et al., 2018). This strategy is dependent on the availability of fine-scaled historical yield maps and records of crop-type spatial distribution for instances where VI's, often NDVI, are used as input features. Constraints for this strategy include its applicability to a limited range of crops, as certain crops are more suitable for this type of yield prediction due to their specific plant traits. When using NDVI as a biomass indicator, crops with a high leaf area index pose challenges because NDVI tends to saturate beyond a certain threshold (~0.8), reducing its sensitivity and accuracy for estimating biomass. Despite these limitations, this method can still be highly effective when its constraints are carefully considered. For example, Lai et al. (2018) achieved high accuracy in yield prediction for wheat in Australia using Landsat data. Similarly, Gavahi et al. (2021) used this approach with MODIS data to train a deep learning model (DeepYield), which demonstrated superior performance compared to other tested machine learning models. DeepYield is particularly effective at capturing inherent spatiotemporal patterns of large-scale datasets (Gavahi et al., 2021). With its 1 km resolution, this model is best suited for analyzing larger regions, making it valuable for LULC planning by policymakers or regional managers. Using a machine learning approach to derive empirical relationships for yield provides a data-driven approach that is both scalable and flexible, though the accuracy of the model is highly dependent on high-quality, extensive datasets of ground truth observations for training and validation purposes.

Since high-quality, extensive datasets of actual harvested yield are nearly impossible to obtain, machine learning approaches can luckily also be integrated into other facets of crop monitoring. Automated collections of current-season RS data can be used in machine-learning models focused on crop disease monitoring to detect problematic conditions. NDVI derived from high-resolution PlanetScope satellite imagery (3 m resolution) has been shown to effectively detect the presence of soybean Sudden Death Syndrome (SDS), as early signs of the disease include leaf yellowing or browning, which is easily captured by NDVI changes (Raza et al., 2020). This early detection capability allows for targeted interventions at the field level, minimizing the spread of the disease. Alternatively, MODIS data, with its coarser resolution but broader spatial coverage, can be used to identify regions at risk for SDS on a larger scale. This would enable the implementation of preventative measures such as crop rotation strategies or the use of resistant soybean varieties in areas heavily dominated by soybeans. By proactively addressing potential hotspots, MODIS-based detection can help prevent widespread SDS epidemics and support sustainable disease management practices (Yang et al., 2016).

Agriculture faces the challenge of balancing food security with environmental sustainability, requiring advanced LULC mapping to optimize crop distribution and resource use. LULC mapping is highly effective in providing historical insights into landscape changes and detecting crop rotation patterns, which are critical for large-scale planning that promotes sustainable management. As a key component of LULC mapping, accurate crop classification enables LULC planning to function as a valuable tool for supporting large-scale, coherent collaboration across agricultural and environmental sectors. By integrating these capabilities, LULC mapping becomes instrumental in achieving sustainable agricultural practices.

6. Future research

The applications of satellite data in agriculture remain largely centered on analyzing recent trends, enhancing in-season tools for farmers, and supporting policy decisions. This review highlights that RS data already holds significant potential as a valuable resource in advancing a green transition within the agricultural sector. Existing tools and methods can be adapted to align with diverse goals, serving as effective monitoring systems to evaluate sustainable management practices. These systems can also support actions like NbS to mitigate nutrient pollution and other anthropogenic pressures, contributing to more sustainable and resilient agricultural landscapes.

While the advantages of RS applications in agriculture are significant, a few challenges and limitations must be carefully addressed when implementing RS-driven solutions. Firstly, modeling with big data often requires complex frameworks capable of capturing the entire perspective, which can lead to a black box scenario. In such cases, when machine learning or deep learning approaches are employed to detect patterns in RS data, the internal workings and decision-making processes of the model remain unclear. This lack of transparency can result in reduced trust in the model's reliability and output. Secondly, the combination of complex models and the technical expertise needed to handle satellite imagery presents a significant hurdle (Sishodia et al., 2020). Although satellite data is often freely available, extracting meaningful agricultural insights from it demands an advanced technical skill set, making its utilization less accessible to non-experts. Third, the availability of ground truth data or labels for training scenarios is a significantly limiting factor when combining RS with machine or deep learning approaches. High-quality and extensive datasets are often difficult to obtain, which poses a challenge for developing accurate and reliable models. Fourth, selecting RS sources requires making informed decisions on resolution needs, revisit frequency, and sensor or data type. These decisions often involve trade-offs: higher resolution typically comes at a higher cost (e.g., using airborne or proximal sensors) or entails lower revisit frequency (Peng et al., 2021). The optimal selection depends heavily on the scale and purpose of the study. Fortunately, advancements in satellite data acquisition, especially with the launch of Sentinel-1 and Sentinel-2 missions, have significantly improved both resolution and revisit frequency, making high-quality RS data more accessible. Fifth, although satellite revisit times are advantageous for long-term studies compared to the on-demand availability of airborne or proximal sensors, optical satellites face significant limitations due to cloud cover, which can interrupt data acquisition. As a result, filtering, quality assurance, and preprocessing of raw data are essential steps before integrating it into a model (Zhang et al., 2022). Lastly, satellite imagery represents the world in pixels, which can introduce noise from infrastructure or other irrelevant elements, particularly in studies focused on cropland. To address this, research is often more effective when conducted in masked areas where random noise can be filtered out. This involves obtaining or creating a masking filter to isolate areas of interest. Additionally, determining whether the model output should be pixel-based or object-based is a critical consideration that must be addressed before model evaluation and assessment (Zelaya et al., 2016).

In our view, the primary focus of future research should be on refining and automating RS tasks to develop standardized, user-friendly methods for monitoring. These advancements, supported by software developers, could result in practical tools for data-driven decision-making at various levels, including farms, regions, and policymaking. In many cases, RS data can provide sufficient status assessments, potentially replacing extensive manual field studies that require significant funding and labor. However, there are still limitations to the utility of satellite data in its current state of available products. For instance, resolutions of 20–30 m per pixel are not ideal for analyzing small-scale features such as smaller farms, plots, or biodiversity strips along fields (Quinton and Landrieu, 2021). Luckily, the field of satellite technology is continually evolving. Another challenge lies in crop classification models: while they have become adept at identifying a wide range of crops, including grasslands as a general class, they still struggle with more specific categories such as vegetables, cattle grazing, meadows, vineyards, and orchards (Begue et al., 2018; Quinton and Landrieu, 2021). Addressing these gaps remains a key focus for future advancements.

7. Conclusions

This review offers a perspective on promoting transitions towards sustainable agricultural management and implementing mitigation solutions such as NbS within the framework of current RS applications in agriculture. Rather than providing an exhaustive overview of all potential RS applications in the field, our aim is to present fresh perspectives on a selected range of existing applications. This approach is reflected in our literature research, which specifically targeted studies utilizing satellite RS data either as a primary source or as a significant component of their datasets, offering insights into its practical applications in agriculture. The final selection of studies highlights the potential of RS technologies in tackling critical challenges such as nutrient management, soil degradation, water pollution, environmental impacts, and sustainable agricultural planning.

Key findings indicate that RS data already plays a crucial role in monitoring and optimizing nutrient management practices. Utilizing multisource data allows agricultural stakeholders to gain deeper insights into the negative impacts of unsustainable practices, such as monocropping and intensive tillage, which contribute to soil degradation and nutrient leaching. The studies reviewed highlight the significance of adopting sustainable practices, including crop rotation, reduced tillage regimes, and minimizing bare fallowing, to improve soil quality and nutrient retention. This further underlines the need for effective monitoring of these sustainable practices and the transition towards such practices. RS-based methods have proven highly effective in monitoring and assessing these practices across large spatial and temporal scales, offering valuable support for informed decision-making in sustainable agriculture.

Despite the advancements in RS applications, challenges remain in terms of data accessibility, processing complexities, and the need for high-quality ground truth data. Moreover, while satellite data offers cost-effective and scalable solutions, limitations related to resolution, revisit frequency, and data gaps due to cloud cover still pose significant barriers. Future research should focus on refining methodologies that integrate RS data with emerging technologies such as machine learning to improve model accuracy and applicability across diverse agricultural landscapes. Emphasis should also be placed on developing user-friendly, automated RS pipelines and tools to enhance accessibility and practical implementation. The integration of RS data in agricultural management presents significant opportunities for improving sustainability while still considering the implications for involved stakeholders. Addressing the existing challenges and investing in technological innovations will allow RS to become a highly valuable tool, facilitating data-driven decision-making and promoting long-term sustainability in agriculture.

CRediT authorship contribution statement

Maria S. Vesterdal: Writing – review & editing, Writing – original draft, Project administration, Methodology, Investigation, Conceptualization. **René Gislum:** Writing – review & editing, Validation, Supervision, Resources, Conceptualization. **Tommy Dalgaard:** Writing – review & editing, Validation, Supervision, Resources, Conceptualization.

Declaration of competing interest

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

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Appendix

A1: Table of the keywords used in the literature exploration searches. The final search and inclusion were performed on the 3rd of October 2024, though alerts of the search have been monitored up until submission. The search used for this review contained the following keywords emphasized in bold.

Topic 1 *Management parameters*	Topic 2 *Data type*	Topic 3 *Research field*	Topic 4 *Irrelevance*
Biobased fertili*	**Multisource data**	**Agriculture**	**Aquatic**
Bio-based fertili*	**Remote sen***	**Crop***	**Building**
Biomass	**Satellite imag***	Environment	**City**
Crop rotation	**Sentinel***		**Grey**
Green biorefin*			**Marine**
Nature-based solution*			**Natural disaster**
Nbs			**Natural hazard**
NDVI			**Roof**
Nutrient management			**Urban**
Permanent grass			**Wall**
Soil protect*			
Water quality			

A2: Table of the final selection of content papers used to discuss the current applications of remote sensing in agriculture and their potential for being reframed for sustainability goals.

Authors	Paper	Year
Ahmed et al.	An examination of thematic research, development, and trends in remote sensing applied to conservation agriculture	2024
Amin et al.	Multi-Season Phenology Mapping of Nile Delta Croplands Using Time Series of Sentinel-2 and Landsat 8 Green LAI	2022
Begue et al.	Remote Sensing and Cropping Practices: A Review	2018
Blickensdörfer et al.	Mapping of crop types and crop sequences with combined time series of Sentinel-1, Sentinel-2 and Landsat 8 data for Germany	2022
Estel et al.	Mapping cropland-use intensity across Europe using MODIS NDVI time series	2016
Fan et al.	Winter cover crops in Dutch maize fields: Variability in quality and its drivers assessed from multi-temporal Sentinel-2 imagery	2020
Gavahi et al.	DeepYield: A combined convolutional neural network with long short-term memory for crop yield forecasting	2021

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(*continued*)

Authors	Paper	Year
Giordano et al.	Improved Crop Classification with Rotation Knowledge using Sentinel-1 and -2 Time Series	2020
Gokkaya et al.	Subsurface tile drained area detection using GIS and remote sensing in an agricultural watershed	2017
Gu et al.	Mapping marginal croplands suitable for cellulosic feedstock crops in the Great Plains, United States	2017
Hagen et al.	Mapping conservation management practices and outcomes in the corn belt using the operational tillage information system (Optis) and the denitrification–decomposition (DNDC) model	2020
Heal et al.	A Probabilistic Approach to Mapping the Contribution of Individual Riverine Discharges into Liverpool Bay Using Distance Accumulation Cost Methods on Satellite Derived Ocean-Colour Data	2023
Huang et al.	Exploring the potential of multi-source satellite remote sensing in monitoring crop nutrient status: A multi-year case study of cranberries in Wisconsin, USA	2024
Kandziora et al.	Detecting land use and land cover changes in Northern German agricultural landscapes to assess ecosystem service dynamics	2014
Kussul et al.	Crop inventory at regional scale in Ukraine: developing in-season and end-of-season crop maps with multi-temporal optical and SAR satellite imagery	2018
Lai et al.	An empirical model for prediction of wheat yield using time-integrated Landsat NDVI	2018
Liu et al.	Climate impact from agricultural management practices in the Canadian Prairies: Carbon equivalence due to albedo change	2022
Machichi et al.	Crop classification using machine learning and remote sensing data	2023
Marion et al.	Associations between county-level land cover classes and cyanobacteria blooms in the United States	2017
Minhoni et al.	Multitemporal satellite imagery analysis for soil organic carbon assessment in an agricultural farm in southeastern Brazil	2021
Mueller-Warrant et al.	Remote sensing classification of grass seed cropping practices in western Oregon	2011
Peltonen-Sainio et al.	Pre-crop Values From Satellite Images for Various Previous and Subsequent Crop Combinations	2019
Peng et al.	Random forest regression results in accurate assessment of potato nitrogen status based on multispectral data from different platforms and the critical concentration approach	2021
Pepe et al.	Mapping spatial distribution of crop residues using PRISMA satellite imaging spectroscopy	2022
Pichura et al.	The Impact of Pre-Crops on the Formation of Water Balance in Winter Wheat Agrocenosis and Soil Moisture in the Steppe Zone	2024
Pinto et al.	Including cover crops during fallow periods for increasing ecosystem services: Is it possible in croplands of Southern South America?	2017
Quinton et al.	Crop Rotation Modeling for Deep Learning-Based Parcel Classification from Satellite Time Series	2021
Raza et al.	Exploring the Potential of High-Resolution Satellite Imagery for the Detection of Soybean Sudden Death Syndrome	2020
Shea et al.	Using remote sensing to identify liquid manure applications in eastern North Carolina	2022
Simms et al.	The application of time-series MODIS NDVI profiles for the acquisition of crop information across Afghanistan	2014
Sishodia et al.	Applications of Remote Sensing in Precision Agriculture: A Review	2020
Victor et al.	Remote Sensing for Agriculture in the Era of Industry 5.0 - A Survey	2024
Waldhoff et al.	Multi-Data Approach for remote sensing-based regional crop rotation mapping: A case study for the Rur catchment, Germany	2017
Waldner et al.	Needle in a haystack: Mapping rare and infrequent crops using satellite imagery and data balancing methods	2019
Wan et al.	Mapping agricultural tile drainage in the US Midwest using explainable random forest machine learning and satellite imagery	2024
Weiss et al.	Remote sensing for agricultural applications: A meta-review	2020
Yang et al.	Assessing Field-Specific Risk of Soybean Sudden Death Syndrome Using Satellite Imagery in Iowa	2016
Zelaya et al.	Characterization and analysis of farm system changes in the Mar Chiquita basin, Argentina	2016
Zhang et al.	Towards automation of in-season crop type mapping using spatiotemporal crop information and remote sensing data	2022
Zhou et al.	Crop Classification and Representative Crop Rotation Identifying Using Statistical Features of Time-Series Sentinel-1 GRD Data	2022

Data availability

No data was used for the research described in the article.

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