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Review

Review of Applications of Remote Sensing towards Sustainable Agriculture in the Northern Savannah Regions of Ghana

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Abstract: This paper assesses evidence-based applications of Remote Sensing for Sustainable and Precision Agriculture in the Northern Savanna Regions of Ghana for three decades (1990–2023). During this period, there have been several government policy intervention schemes and pragmatic support actions from development agencies towards improving agriculture in this area with differing level of success. Over the same period, there have been dramatic advances in remote sensing (RS) technologies with tailored applications to sustainable agriculture globally. However, the extent to which intervention schemes have harnessed the incipient potential of RS for achieving sustainable agriculture in the study area is unknown. To the best of our knowledge, no previous study has investigated the synergy between agriculture policy interventions and applications of RS towards optimizing results. Thus, this study used systematic literature review and desk analysis to identify previous and current projects and studies that have applied RS tools and techniques to all aspects of agriculture in the study area. Databases searched include Web of Science, Google Scholar, Scopus, AoJ, and PubMed. To consolidate the gaps identified in the literature, ground-truthing was carried out. From the 26 focused publications found on the subject, only 13 (54%) were found employing RS in various aspects of agriculture observations in the study area. Out of the 13, 5 studies focused on mapping the extents of irrigation areas; 2 mapped the size of crop and pasturelands; 1 focused on soil water and nutrient retention; 1 study focused on crop health monitoring; and another focused on weeds/pest infestations and yield estimation in the study area. On the type of data, only 1 (7%) study used MODIS, 2 (15%) used ASTER image, 1 used Sentinel-2 data, 1 used Planetscope, 1 used IKONOS, 5 used Landsat images, 1 used Unmanned Aerial Vehicles (UAVs) and another 1 used RADAR for mapping and monitoring agriculture activities in the study area. There is no evidence of the use of LiDAR data in the area. These results validate the hypothesis that failing agriculture in the study area is due to a paucity of high-quality spatial data and monitoring to support informed farm decision-making.

Keywords: precision agriculture; sustainable farming; UAVs; earth observation; satellite imagery; northern Ghana

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1. Introduction

Globally, there is a steady rising demand for agriculture products and raw materials beyond the traditional fiber and nutrition industries. This demand comes from feedstock, energy, industrial products, and pharmaceutical products in response to the needs of modern life [1,2]. Thus, global giant farming countries such as Turkey, Australia, USA, and India are modifying their methods of operations and production in order to respond to this growing global demand for agricultural product supplies [3,4]. Large productions from these countries are supplied to developing countries in Africa, Southeast Asia, and

Latin America. This trend in supplies demonstrates that countries in the global south have deficits of agricultural products for global supplies [5]. These deficits are attributed to lack of capital for agriculture expansion [6] and the underperformance of the agriculture sector due to climate change, urbanization, and steady population growth [7–9]. Accordingly, there is a surge in food security issues in these regions. Yet technological advancement, such as the use of remote sensing (RS), has enhanced agriculture performance in advanced countries [10–13]. However, the extent to which RS has been used to support sustainable agriculture in the Cereal Root—Mixed Farming Systems (CR-MFS) areas in the Northern Savannahs of Ghana is not known.

Like other West African countries, Ghana's economy is largely agricultural [14,15]. Ghana's agriculture industry mainly consists of raising animals, planting trees, fishing, producing food, and cash crops [7]. Over 30% of Ghana's GDP comes from this sector and its associated agro-industry. The sector employs about 33% of the country's total labor force and over 76% in rural regions [16]. In the rainforests and Savannah ecological zones, the primary agricultural activities are food and cash crop cultivation, along with livestock rearing, whereas the primary agricultural activities in the coastal areas are fishing and limited food crop farming [17]. Due to the double maxima rainfall experienced in the rainforest ecological zone, food and cash crops such as maize, cashew, cocoa, plantain, and timber are grown and harvested twice a year [18]. A protracted drought is also experienced in the Northern Savannah Regions, with single annual maxima of rainfall [19]. This physiological state limits evergreening, fish farming, cocoa cultivation, and timber harvesting in the Savannah ecological regions of Ghana. Thus, large-scale food crop farming is the predominant farming activity in the Northern Savannah Regions due to their relatively level terrain and rich soils [20]. In history, the region has consistently provided food, meat, and dairy products to suit Ghana's increasing meat and grain demand.

Evidently, the Northern Savannah Regions are predominantly rural, with over 60% of the total population living in rural areas, where the dominant activities are livestock rearing and food crop growing [20–22]. The dominant food crops grown in this region, with cognisance to their biophysical characteristics, are cereals and root crops. Farmers in this region have historically engaged in bush fallowing, single cropping, shifting cultivation, and crop rotation in response to the biophysical characteristics of the area [20]. However, due to factors such as rapid urbanization, shifting dietary demands, recent climate change, and their combined effects on land use, land cover, and land degradation, the availability of arable land for food crop cultivation in the Northern Savannah Regions has become limited [8,23]. To adapt to the incipient circumstances and build resilience, farmers in the area have embraced mixed farming (livestock rearing in addition to food crop farming) and mixed cropping [24,25]. Yet livestock populations and farm food crop yields are failing, increasing food security issues in the area. In the past three decades, the Ghanaian government, in partnership with its development partners, including the European Union (EU), the Food and Agriculture Organization (FAO), the African Development Bank (AfDB), and the International Fund for Agricultural Development (IFAD), has implemented various initiatives aimed at enhancing agricultural performance in the area [23]. "EU Food Security Response in Northern Ghana", "Northern Rural Growth Programme", "Inland Valley Rice Development Project", "Small-Scale Irrigation Development Project", "Planting for food and jobs", and "one-village-one-dam" programs are a few examples of such projects.

However, there are significant gaps in knowledge that impact both the establishment of initiatives and the attainment of goals towards enhancing agricultural performance in the Northern Savannah Regions. In this regard, statistics help with the development and implementation of intervention projects and are crucial in setting baselines for informed policy decision-making. Geospatial technologies, or technical innovations in space and on land, have revolutionized many aspects of a nation's economy in the twenty-first century, including agriculture. Yet, there is limited knowledge on how these technologies, such as remote sensing (RS), have been used to generate pertinent data for localized improvements to CR-MFS in Ghana's Northern Savannah Regions. RS, in particular, is useful in continuous monitoring and measurement of the spatial extents of farmland dynamics and associated drivers for improving resilience, encouraging precision farming, and addressing land fertility issues in the CR-MFS areas. Thus, the past intervention schemes in the area have used top-down approaches that frequently ignore baseline observations and consistent monitoring of biophysical parameters to determine farm needs, the status, and trends of basic databases such as soil water and nutrient retention, farmland extents, irrigation potentials, weeds, and pest infestations. This has led to low success stories from intervention schemes in the area.

Although some of this data and information may already be available, it is usually not designed to align with targets for sustainable agriculture in the CR-MFS [26]. Although sustainable CR-MFS is becoming more complex, the levels of requisite data for understanding and addressing these complex challenges are inadequate [8,23]. To address these knowledge gaps and complexities, therefore, this paper assesses the application of RS tools and techniques in support of sustainable and precision agriculture in CR-MFS areas in the Northern Savannah Regions of Ghana for the period 1990–2023. Unambiguously, the study assesses general applications of RS for: (1) examining raw agriculture field baseline data; (2) mapping irrigation farming extents and performance; (3) cropland and rangeland monitoring and measurement of yields; (4) farmlands degradation detection and monitoring; and (5) weeds and pests' management for sustainable and precision agriculture in the study area. The succeeding sections provide details on the methodology employed, state of the art, findings and discussions, and conclusions.

2. Materials and Methods

2.1. Study Area

The study was conducted primarily in the Savannah agroecological zone that cuts across four administrative regions of Ghana (Figure 1), namely the Northern (11 communities), Upper East (9 communities), Upper West (13 communities), and Savannah Regions (1 community). These regions fall within latitude 8°0′0″ N to 11°0′00″ N and longitude 0°1′00″ E to latitude 3°0′00″ W (Figure 1).

The vegetation in the Savannah parts of Ghana is predominantly semi-arid, characterized by Guinea Savannah. However, traits of the Sudan Savannah are observed in areas around Bawku. The vegetation in the area consists of grassland with clusters of drought-resistant trees such as baobabs, shea butter, or acacias, which can be used for agroforestry. Generally, this region is notably drier than the southern parts of Ghana throughout most of the year. Consequently, the climate in this area is marked by significant inter-annual and multi-decadal variability, manifesting in alternating long periods of dry and short wet/rainfall conditions occurring in a year [27]. Thus, the Northern Savannah Regions of Ghana exhibit an unpredictable rainfall pattern marked by substantial variations in terms of onset, quantity, and coverage from one season to another [19]. The area experiences a unimodal rainfall pattern, which occurs between May and October every year, with records ranging between 500 mm and 1200 mm [28]. The mean monthly temperature ranges from 27 °C to 36 °C [19]. CR-MFS is the predominant farming method practiced in the area [23]. The cereals grown in this area include millet, sorghum, rice, and maize, while the leguminous crops include cowpea, groundnut, and soybean. The root crops include cassava, cocoyam, potatoes, and yam. The Northern Savannah regions have a great potential for farming and are noted as the food basket of the country [8]. The region has a comparatively low population density in rural areas but gradually denser in urban and per-urban areas.

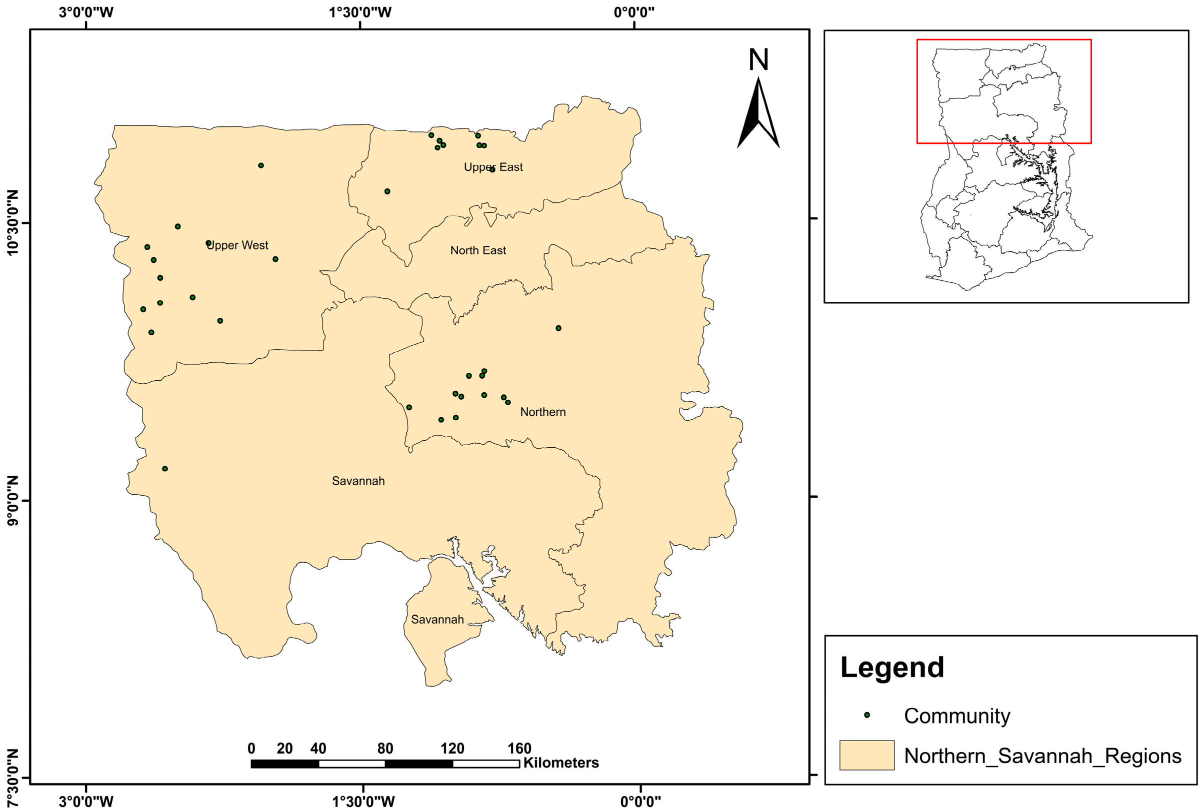

Figure 1. Map of Study Area.

2.2. Literature Review

The study aimed to investigate the application of RS technologies for enhancing sustainable agriculture and resilience building in CR-MFS areas in Ghana's Northern Savannah Regions. To this end, a systematic appraisal of scientific and gray literature was carried out. The literature review comprises a desk analysis of publications and unpublished works. Various publications from scientific and non-scientific works, both peer-reviewed and opinion papers, commentaries, and technical reports from different Ghanaian government agencies, UN agencies, non-governmental organizations (NGOs), and community-based organizations (COs) that support sustainable agriculture development in the study area were retrieved and analyzed. The Internet (including Google searches), personal and research group databases, PubMed, Web of Knowledge, Science Direct, Web of Science, ResearchGate, and Google Scholar are some of the literature repositories that have been searched for materials that are relevant to the current study.

The following keywords and search query phrases are used for robust returns in each database query, both separately and in combinations: "Remote sensing of farmlands in Northern Ghana", "Satellite data inventory of agriculture in the northern regions of Ghana", "mapping farmlands of northern Ghana", "mapping irrigation areas of the Upper West Region of Ghana", "mapping irrigation areas of Upper East Region of Ghana", "Applications of Remote Sensing on farmland monitoring in Northern Ghana", "Remote Sensing for precision agriculture in the Northern Regions of Ghana", "Remote Sensing Agriculture in the Northern part of Ghana", "UAVs for farmland management in Northern Regions of Ghana", "Application of Unmanned Aerial Vehicles for farmland monitoring in Northern Regions of Ghana", "monitoring crop performance in the Northern Region of Ghana using satellite imagery", "monitoring crop performance in the Upper West Region of Ghana using satellite imagery", "monitoring crop performance in the Upper East Region of Ghana using satellite imagery", "monitoring crop performance in the North-East Region of Ghana using satellite imagery", and "monitoring crop performance in the Savannah Region of Ghana using satellite imagery".

It was discovered that multiple publications discuss the use of remote sensing technologies to generate data on these variables during the search for the most pertinent literature. All but a few, nevertheless, who have case studies in Ghana's northern regions were downgraded in this research. Any study that addressed the spatial analysis of agriculture, sustainable land management generally, or LULCC and LD in Ghana without addressing the CR-MFS areas in Ghana's Northern Savannah Regions was disqualified from consideration. Following works on the use of systematic literature review methods [29,30], only 30 of the 110 published journal papers, books and book chapters, reports, and communications that were retrieved from the databases were screened to identify the most pertinent studies that addressed the objectives of this study.

2.3. Fieldwork

In 4 of the 5 Northern Regions, fieldwork and ground truthing operations were carried out. Field inspections revealed that the farmers' adopted Land Use and Land Cover Changes (LULCC) and their impact on cropping performance, vegetation health, water availability, soil water retention capacity, erosion, and drivers were of special interest. The CGIAR Mixed Farming Systems Initiative (MFS; https://www.cgiar.org/initiative/mixed-farming-systems/ (accessed on 2 December 2023)) utilized a baseline survey to choose the communities that were visited. The 34 communities spread over Ghana's four northern regions make up this group (Figure 1). The project contact numbers in each of these communities were supplied by the Institute of International Tropical Agriculture (IITA) office in Tamale. The visit was communicated to all the contact people. Community members and contacts were informed about the goals and purpose of the fieldwork in exchange for their voluntary consent. The community entry protocol and all ethical guidelines were followed. To achieve the field visit's goals, a mix of qualitative and quantitative data collection techniques was employed. These include:

1. Conduct direct observation to note LULC characteristics, environmental conditions, and agricultural related land use activities.
2. Interviews and surveys with local communities and stakeholders through focus group discussions and key informant interviews.
3. Data collection tools (ODK (open source) embedded with voice recorders, cameras, and GPS) devices were used to record and document field observations and geotag locations.
4. Analysis and comparison of field data with existing data recovered from the literature to assess the methods, key findings, and gap identification.

3. Literature Review on Global Applications of Remote Sensing in Agricultural Activities

The history of the use of RS in agriculture started with its wider applications for natural resource inventory and development, largely in North America, Europe, Australia, and Eastern Asia [29–32]. Since the late 1940s, spaceborne sensors have been used to provide the spatial resolution required for monitoring natural resources and natural capital growth in these regions [33,34]. Black and white aerial photography was the primary RS tool used [31,35]. However, in recent times, there have been rapid advances in sensors and computers, which have expanded the utility of RS in agriculture monitoring, mapping, and measurement [36]. These improvements include higher spatial resolution, hyperspectral data, and the recent use of RADAR and LiDAR platforms, allowing more detailed mapping [37] and monitoring of agriculture activities [30,38]. Hence, new computer applications and techniques are being developed for enhancing precision, smart, and sustainable agriculture [39]. These techniques employ features embedded in commercial image processing software, such as ArcGIS, ERDAS IMAGINE, IDIRISI, and ENVI (all versions) as well as free and open-source programs like QGIS (Version 3.28.12, all versions). They are applied to discern suitable cultivable lands, identify irrigation sites, assess pasturelands, understand the interplay between crop growth, health, and water management, track animal movements, estimate production, and monitor changes in soil-vegetation-atmosphere-transfer processes over time [40,41]. These tools have been used extensively in Southeast Asia [37], Australia [39], and North America [42].

Despite its potential, the utilization of optical RS imagery in agriculture, particularly in tropical regions, presents several challenges. These include the presence of cloud cover, haze, and crude resolution [30,43]. In many places, where agriculture activities are undertaken only in the rainy season, cloud-free imagery may not be available over some months. This necessitated the use of unmanned aerial vehicles (UAVs), hyperspectral RS, LiDAR, and RADAR, which can retrieve ground data through even thick cloud cover [38,44]. Change detection maps generated with these data help to detect water pollution, drought, crop health, vegetation losses, and weed infestations for the periods when cloud-free data could not be found [45,46]. Such pieces of information can be synthesized and used to appraise the extents and expansions of urban areas and the impacts on agriculture in near real time. For instance, with RADAR interferometry, multiple radar images taken of the same area at different times are used for change detection [33,38,47]. With the current applications of RADAR in agricultural studies, two general approaches are used: InSAR and Repeat Pass Interferometry. While the former typically uses successive RADAR images and pass of the targeted farmland or rangeland to increase the information in a scene, the latter uses RADAR scenes taken over the same area but on different passes of the satellite [45,48]. Nonetheless, the use of RADAR data requires special skills and training that are lacking for many who are interested in using RS for agriculture development in developing countries.

To address these and other related issues, the NASA Land Cover and Land Use Change (LCLUC) program introduced the South/Southeast Asia Research Initiative (SARI). SARI aims to promote and build capacity through the use of RS data to assess the amount of food grown, aboveground biomass availability for fodder and rangeland stocking, and water availability for irrigation farming in a given year [37,49]. Satellite RS observations, in particular, provide daily data on relevant parameters, including rainfall, temperature, vegetation and crop health, and soil moisture conditions. Many large-scale and individual farmers in developed countries use these data to monitor, understand, and diagnose the impacts of climate on agriculture [49]. For instance, the Global Agriculture Geo-monitoring Initiative (GEOGLAM) is an RS-based system developed by USAID and the World Food Programme for monitoring food production in food-insecure regions across the globe [49]. A combination of RADAR data and social and economic food security indicators is a critical asset towards achieving this goal [50,51].

Several other multi-sensor RS models with various capacities have been designed and launched in developed countries for mapping croplands. For instance, Google Earth Engine now hosts a plethora of cropland data modeling products in support of precision agriculture. Precision agriculture is an integration of RS, Global Positioning Systems, and other new technologies for managing agricultural productivity in order to maximize the cost–benefit ratio of production [52,53]. Precision agriculture emphasizes spatial–temporal data analysis and management for robust use of farm inputs, leading to improved crop production and environmental quality [54,55]. It involves advances in RS image processing, field positioning, and sensor design for applications in pre-growth soil fertility, moisture analyses, crop growth, crop monitoring, and yield forecasting [43,56]. The modeling products include the USDA NASS Cropland Data Layer (CDL) and the Global Food Security-Support Analysis Data (GFSAD) Layer [49,57]. These data modeling tools are used to analyze LiDAR, RADAR, and moderate-resolution satellite imagery for measuring cropland extents [58], crop dominance, and water availability [59].

Due to the level of detail and accuracy required in effective precision agriculture, unmanned aerial vehicle (UAV)-based RS have now been used in combination with space-based sensors [60]. In recent times, UAVs have been widely applied in agricultural fields in developed countries to conduct near-real-time soil, forage, crop and pest monitoring, and management. Examples can be found in the works of Bwambale et al. [61], Lamb and Brown [62], and Maes and Steppe [63]. UAVs have been especially identified with the ability to generate timely and accurate weed maps [62,64,65]. An important advantage of UAVs in agriculture is their ability to provide crop-specific data, yield estimates, and soil moisture assessments. For example, Feng et al. [66] used a UAV system to monitor a cotton field at both the flowering growth stage and the pre-harvest stage. This study concludes that UAVs provide robust estimates of cotton yield. Maimaitijiang et al. [67] used a UAV to estimate soybean grain yield at a test site in Columbia, Missouri, USA. The results indicate that UAVs can provide a relatively accurate estimation of crop yield and valuable crop field management with high spatial precision. Furthermore, Yang et al. [68] and Reza et al. [69] used UAVs for rice yield estimation by segmenting grain areas. Their findings are that UAV image-based grain segmentation provides highly accurate and convenient rice yield estimates. Revenga et al. [64] used UAVs to predict above-ground biomass for croplands at a sub-meter resolution.

Applications of Remote Sensing (RS) for Sustainable and Precision Agriculture in Ghana

Empirical analysis of the concept "Sustainable Agriculture" finds that a proper understanding of the concept is context-based, including science and politics [70,71]. For the scientific purpose of this study, refer to the definitions of Feenstra et al. [72], Mason [73], and Reganold et al. [74]. Thus, sustainable agriculture is the continuous production of food crops, the rearing of animals, and the practice of agro-forestry with the efficient use of non-renewable and on-farm resources without compromising environmental quality (biodiversity loss, land degradation, compaction, salinization, and depletion and pollution of water resources) while enhancing the quality of life for farmers and society as a whole. It also comprises efficient farm management procedure practices, also referred to as precision agriculture [75–78]. Thus, in their work: "Examining the potential of open source remote sensing for building effective decision support systems for precision agriculture in resource-poor settings", Kpienbaareh et al. [79] propose that the best way, inter alia, to achieve the objective of sustainable and precision agriculture on cost reduction, improving scarce resource allocation, and increasing farm yields is to adopt the use of RS. This is particularly useful as a decision support system (DSS) for both large-scale and smallholder farmers and commercial and cash-crop farmers in resource-poor regions such as the CR-MFS areas of the Northern Savannah Regions of Ghana [79].

However, using open-source RS data to map smallholder farms in resource-poor areas presents results that are coarser in resolution with compromised accuracy and precision. Such data often fail to capture fragmented small-holder farms in highly heterogeneous landscapes, such as the Northern Savannah Regions of Ghana. To overcome such limitations in their study, Xiong et al. [80] used a combination of Sentinel-2 and Landsat-8 data on Google Earth Engine to map smallholder cropland extents in Africa, including the Northern Savannah Regions of Ghana. The study estimated a total of 313 million hectares (Mha) as the net cropland area of Africa for the nominal year 2015 [80]. Xiong et al. [81] combined very high-resolution satellite imagery (VHRI) and Indigenous Knowledge (IK) to derive near-accurate and precise cropland extents across Africa for the 2014 base year. The study estimated 296 Mha net cropland areas (260 Mha cultivated and 36 Mha fallows), including both rainfed and irrigated. The use of fractional cover approaches in mapping the cropland area in the heterogeneous landscapes of West Africa from multi-temporal Landsat and MODIS data have also been tested by Forkuor et al. [82]. Haile et al. [83] used RS-derived land cover data for the years 1994 and 2014 and cross-sectional survey data in 2014 to examine the location association between LULCC and agricultural productivity in the CR–MFS areas in the Northern Savannah Regions of Ghana. The study found that while urbanization and extensification of agriculture have led to biodiversity and ecosystem losses, there was a significant improvement in crop yield and harvest value [83].

Furthermore, Landsat data, in combination with social surveys, have been used by Braimoh [84] to investigate the influence of urbanization, technology, and macroeconomics on the growth of cropland in Ghana during economic changes. The study finds that the dynamics observed in demographics and macroeconomics have transformed subsistence farming into commercial farming in most Ghanaian farming communities, leading to agricultural extensification [84]. Braimoh and Vlek [85] investigated the effects of land cover changes on soil quality parameters in the Savannah Region of Ghana using Landsat-derived land cover maps for 1984, 1992, and 1999. The study finds that continuous cropping on the same piece of land leads to deterioration in soil quality over a period of time [85]. Pinnington et al.'s [86] study finds that satellite-derived estimates of shallow soil moisture can be used to calibrate a land surface model at regional scales in Ghana. Using the RS rainfall dataset, Pinnington et al.'s [86] study recovered improved estimates of soil texture in the Northern Regions of Ghana after data assimilation. Amanor and Pabi [87] propose the combination of RS and qualitative datasets to assess changes in land use and land cover and the impacts of agricultural modernization and mechanization on the economy and local farming systems in the Bono and Ahafo Regions of Ghana. Therefore, Houssou et al. [24] used Landsat-derived land-cover maps in combination with qualitative data to detect the conversion of arable lands to agricultural uses in four villages in the Guinea Savannah and Transition zones. The study finds a gradual adaptation to agricultural intensification in four villages through increasing adoption and use of precision farming technologies [24].

Developing spatial models for precision farming is desirable for efficient decision-making in areas that are resource-poor and vulnerable to the impacts of climate variability such as flooding [88]. Thus, Gumma et al. [89] developed spatial models for the selection of the most suitable areas for rice cultivation in flood-prone areas in Ghana. The model results show that only 3–4% of the total inland valley wetland areas in Ghana were "highly suitable" and 39–47% were "suitable" for rice cultivation [89]. The study also finds that less than 15% of the total inland valley wetland areas, which are estimated to be about 20–28% of the total land area of Ghana, are currently under cultivation. Considering the potency of such rich land units in terms of soil depth, soil fertility, and water availability, in most places, these agroecosystems are an opportunity for the construction of water reservoirs for irrigation farming practices. However, to ensure effective water management for irrigation farming, the actual carrying capacities of these reservoirs should be known. Thus, Annor et al. [44] used RADAR images with field measurements of 21 small reservoirs to provide an all-year-round monitoring of small reservoir volumes in the Upper East Region of Ghana. Gumma et al. [90] used Landsat ETM+ data and time-series MODIS data to map irrigated agricultural areas, as well as other LULC classes, for Ghana. Compared to the irrigated areas reported by the Ghana Irrigation Development Authority, this study revealed a greater surface area of smallholder reservoirs and irrigated lands (32,421 ha).

Nevertheless, Ghansah et al. [91] executed a binary random forest classification on Sentinel-2 images for five consecutive dry seasons (2015 and 2020) to provide information on the spatial-temporal variations of small water reservoirs for dry season farming in the Upper East Region of Ghana. The analysis revealed about 384 small reservoirs in the study area [91]. Kpienbaareh et al. [79] used Sentinel-2A satellite data to monitor crop health to inform farm management and decision-making at the Tono Irrigation Scheme. This irrigation scheme has been established by the Government of Ghana to promote dry-season food crop production by small-scale farmers in the Upper East Region. Asaana and Sadick [92] used Aster Satellite images and GIS overlays to evaluate the irrigation performance of the Tono irrigation system based on the following selected indicators: overall consumed ratio, relative water supply, relative evapotranspiration, depleted fraction, and crop water deficit. The study finds that seasonal average values of the irrigation performance indicators have poor water delivery systems. To forestall similar challenges in the Upper West Region, Diabene et al. [93] used RS-derived land use and land cover and slope data as key parameters to identify potential areas of small reservoirs for the implementation of the agricultural water management intervention of the government of Ghana. Similarly, Akpoti et al. [94] used land cover data to assess the irrigation potential of Ghana's cocoa-growing areas. The study finds a total area of 22,126 km^2 for cocoa plantations and 125.2 km^2 for smallholder reservoirs within cocoa-growing regions.

Rather than the general perception that agriculture is a rural livelihood activity, and for the poor, marginalized, recent migrants, or women, there are widespread, large-scale, and diverse agriculture activities in urban areas in developing countries. These are mainly for the elite, rich, and non-migrants and supplement urban staple food larders. For instance, Mackay [95] used Landsat imagery to study the forms of urban agriculture within the Techiman Municipality and Tamale Metropolis. The study finds that the two cities have sustained organized irrigated vegetable market gardens, home gardening, and staple foods. These findings are similar to Ghana's larger cities of Accra and Kumasi. Thus, Appeaning Addo [96] used Landsat ETM data to develop an integrated monitoring technique for urban farmlands in Accra. While there is a general perception that urbanization is an affront to agricultural land availability and productivity, Abass et al. [97] deployed Landsat TM 1986 imagery, ETM+ 2004 imagery, and Landsat 8 OLI/TIRS imagery in 2016 to examine the effects of peri-urbanization on arable land in the Kumasi Metropolis of Ghana. The results show a strong positive correlation between urban expansion, the size of arable land, and crop output in the Metropolis in the last 30 years.

Furthermore, Boateng and Mensah [98] used Landsat TM 2002 and ETM+ 2015 images to assess the LULC dynamics of Tarkwa-Nsuaem Municipality of Ghana and their impacts on urban agriculture. The study finds a loss of crop and pasturelands to the built environment. Abubakari et al. [99] also used Landsat TM 200 imagery, ETM+ 2010 imagery, and Landsat 8 OLI/TIRS imagery for 2020 to assess the effects of urbanization on arable lands in the Sagnarigu Municipality near Tamale in Ghana. The study finds that the built-up area in the municipality increased from 13.0 km^2 in 2000 to 97.5 km^2 in 2020. Conversely, using Sentinel-2-derived NDVI patterns of selected cocoa farms for November and December 2018 and January 2019, Anyimah et al.'s [100] study finds a predominance of very healthy and healthy cocoa plantations against perceived stressed cocoa farms in Offinso North District and Offinso Municipality. Chemura et al. [101] combined Landsat data and regression techniques to determine the age of oil palm plantations in the Ejisu-Juaben Municipality of Ghana. Yiran et al. [102] used Landsat images between 2000 and 2020 to assess sustainable agriculture in Ghana, using mango farming in the Shai Osu-Doku and Yilo-Krobo Districts of Greater Accra and Eastern Regions, respectively, as a case study. The study finds that agroforestry development contributes to carbon sequestration, air filtering, and soil conservation.

4. Results

Details of the literature studied within the research area are shown in Table 1. The array of research demonstrates the long history of RS technology applications in conjunction with agricultural practices worldwide, which include the work However, it is only recently that these technologies have been directed again toward the monitoring of agricultural activities in Ghana [89]. The Ghana Environmental Resources Mapping Project was the first to classify most of the country's northern regions into twelve classifications based on land cover [103–105]. Although the data have proved helpful since the project's inception, agricultural areas are not the focus. The Northern Regions' LULC has been mapped by later research in a variety of locations, including agricultural fields [103,106,107].

Table 1. Application of remote sensing in support of sustainable agriculture in the Northern Savannah Regions of Ghana.

Ref No.	Objectives and Methods	Findings	Study Area
[79]	Objective: to demonstrate the potential of open source remote sensing (OSRS) for monitoring crop health and development to build an effective decision support system (DSS) for precision agriculture in resource-poor settings. Methods: focused on the Tono Irrigation Scheme, utilizes freely available satellite data (Sentinel-2A).	Using open source remote sensing presents a feasible and practical approach towards building cost-effective and efficient DSSs for farmers in resource-poor settings.	Upper East Region
[83]	Objective: uses information from cross-sectional surveys and remote sensing to examine the connection between changes in land use and cover and agricultural productivity in Northern Ghana. Landsat 5 and Landsat 8 satellite pictures, which cover the whole Northern Ghana region, were used to create the land cover classification for the years 1994 and 2014.	According to this study, land areas that have been converted from natural cover to productive use had greater harvest values (1021 Ghanaian Cedi) and maize yields (0.17 tons per hectare) than land areas that have been converted from bare soil to productive cover. Compared to 1994's barren soils, areas planted with savannah or shrubs were more productive in 2014.	Northern Region
[84]	Objective: The impact of macroeconomic changes on land-use change in Ghana throughout economic reforms was the main subject of this study. Methods: combines sociological surveys and data from remote sensing to determine how market, technological, and demographic factors affect the expansion of farmland during Ghana's economic changes. pictures from Landsat TM from 1984, 1992, and 1999 were used.	Macroeconomic shifts caused farming to become more commercially oriented as domestic production replaced imports as the primary source of food. Following structural adjustment, cropland change is explained by demographic factors. There are six different types of land cover: water, built-up surfaces, grassland, farmland, open woodland, and closed woodland.	Northern Region
[85]	Objective: In a northern Ghanaian location, the effects of changing land cover on soil quality measures were investigated. Landsat Thematic Mapper (TM) maps covering the years 1984, 1992, and 1999 were employed in the study. A digital elevation model built using the study area's contour lines at a 50-foot vertical interval provided the slope and elevation data for the sampling spots.	Between the properties of soils with natural vegetation and soils under cultivation as of 1992, there were no appreciable differences. On the other hand, soils that were permanently farmed (1984–1999) had substantially worse physical and chemical characteristics.	Northern Ghana

Table 1. *Cont.*

Ref No.	Objectives and Methods	Findings	Study Area
[88]	The objective: to address the increasing climate variability and the challenge of accessing water, which pose major impediments to rainfed agricultural productivity in the region. Methods: use of ASR-based techniques using remote sensing and GIS-based MCDA. Utilizes remote sensing and GIS techniques to evaluate various criteria, including geological indicators, subsurface criteria, and land use, to determine suitable areas for ASR technology.	Specifically, challenges related to accessing irrigation water and flooding of farmlands could be effectively addressed by implementing adaptive water management (AWM) technologies throughout the region, significant to improving agricultural sustainability and resilience.	Northern Savannah Regions of Ghana
[89]	Objective: to create spatial models and show how to utilize them to determine which inland valley (IV) wetland rice-growing locations are most suitable. Method: use Landsat imagery.	Given that just a small portion (<15% overall) of Ghana's total IV wetland areas—roughly 20–28% of the country's total geographic area—are now used for agriculture, despite the fact that these land units are extremely rich in terms of soil fertility, depth, and availability of water.	Entire Country + Northern Region
[44]	Objective: to address the challenge of mapping small reservoirs in the Upper East Region of Ghana, which is a critical issue for water resource management and agricultural development in the region. Methods: the use of radar imagery (ENVISAT ASAR) to identify and map small reservoirs.	The study highlights the potential of radar imagery for the identification and mapping of small reservoirs in a semi-arid environment, which can help improve water resource management and agricultural development in the region.	Upper East Region
[90]	Objective: to use remote sensing to map irrigated agricultural regions and describe procedures and guidelines. Techniques: Time-series moderate resolution imaging spectroradiometer (MODIS) data and Landsat enhanced thematic mapper (ETM+) data were used.	The LULC class's NDVI pattern's temporal fluctuations were utilized to distinguish between areas that were and were not irrigated. Because irrigated areas have a guaranteed water supply, long-duration irrigated crops showed more consistency in the temporal fluctuations in the NDVI pattern than short-duration rainfed crops. The Irrigation Development Authority (GIDA) of Ghana reported irrigated areas that were 20–57% lower than the 32,421 ha irrigated area that was estimated via remote sensing.	Northern Region

Table 1. *Cont.*

Ref No.	Objectives and Methods	Findings	Study Area
[91]	Objective: to assess the spatial-temporal variations of the surface areas of small reservoirs in the Upper East Region of Ghana. Methods: use Sentinel-2 satellite imagery.	identified changes in the surface areas of the reservoirs over time.	Upper East
[92]	Objective: to evaluate the irrigation performance of the system based on some selected indicators. Methods: using Aster Satellite image, respectively.	The seasonal average values of the irrigation performance indicators showed that the water delivery system at the Tono irrigation project, based on the selected command areas, is poor. Potential evapotranspiration and actual evapotranspiration were estimated.	Upper East
[93]	Objective: to identify and map suitable areas for the implementation of interventions that can help improve water availability for agricultural activities in the region. Methods: Landat TM and ETM data used.	The results indicate high potential areas of 57.25% and 85.40% for small reservoirs and stone bunds, respectively.	Upper West
[108]	Objective: to generate high-resolution, annual maps of field boundaries for smallholder-dominated croplands in Ghana. Methods: used PlanetWatch data. Converting Planet's daily imagery of the region into two cloud-free composites of the primary growing season and the dry season helps improve classification accuracy by providing seasonal contrast.	The study demonstrated a transferable approach for creating scalable maps of crop field boundaries in smallholder-dominated countries, mitigating errors, and increasing analytical capabilities with machine learning. The resulting maps provide an updated and more granular view of the distribution and extent of croplands in Ghana, complementing existing national and regional land cover maps derived from moderate-resolution imagery.	Upper East Region
[109]	Objective: to identify the potential market acceptance success factors for drone-applied pesticide. Methods: Drones and survey tools.	Farmers became aware of and perceived a high benefit from the use of drone technology to control FAW when compared to the knapsack method.	Northern Region

However, these studies do not aim to categorize croplands, pasturelands, or irrigation systems locally. Therefore, there is much more to learn about the use of LULC mapping for CR-MFS monitoring in Ghana's Northern Savannah Regions.

Figure 2 presents a summary of the applications of RS in support of sustainable agriculture in the Northern Savannah Regions of Ghana.

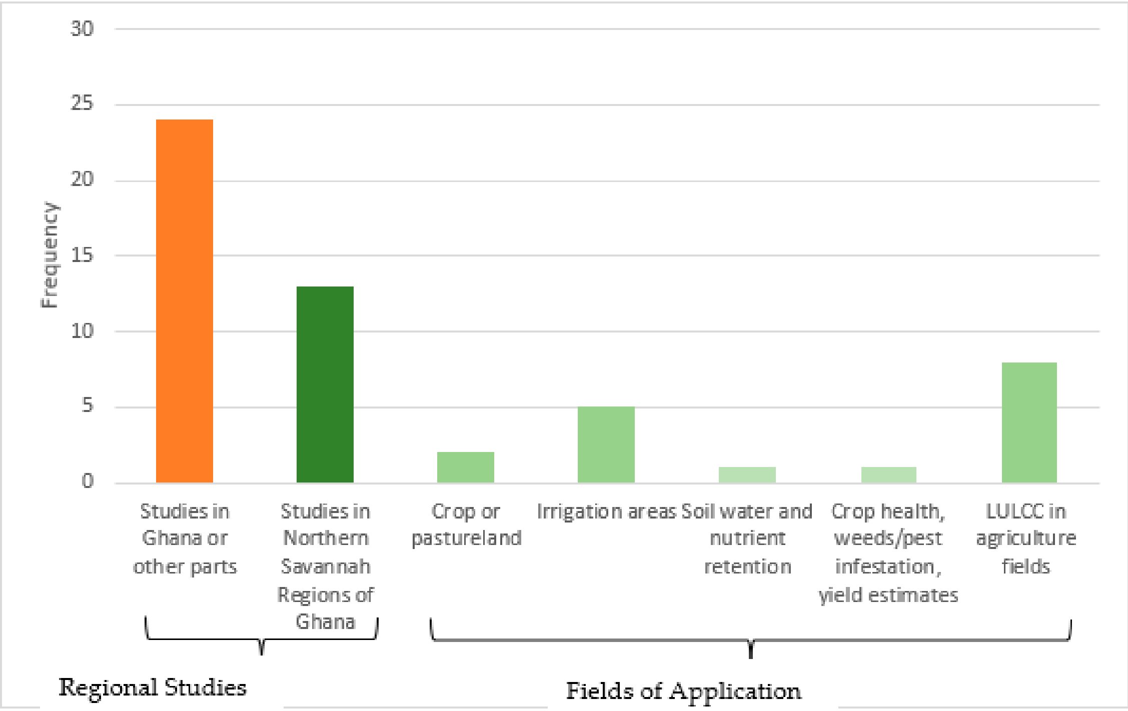

Figure 2. Studies involved with the application of RS to agriculture in Northern Savannah of Ghana.

From the results, it is clear that agricultural mapping using satellite and other RS data remains a challenge in Africa, and in Ghana in particular. Reasons attributed to this phenomenon are the prevalence of a heterogeneous and fragmental landscape, complex crop cycles, and limited access to local knowledge and image processing skills [81]. Consequently, there is no current, consistent, region-wide scheme for routine cropland mapping of the CR–MFS areas of the Northern Savannah Regions of Ghana. As demonstrated in Figure 2, the few studies focused either on the Upper East or Upper West Regions with limited scope and coarse resolution data. Thus, a tailored training and technology transfer program, aimed at accelerating farmers' capacity, acceptance, and implementation of these precision agriculture technologies is recommended. In particular, Agric-extension officers in these areas should initially be targeted for an effective technology transfer. Extension officers should be able to capture and apply RS data for food and water security analysis in order to better guide farmers to make informed decisions. Precise and accurate local cropland extent maps, indicating cropland and non-cropland areas, are starting points. However, precise and accurate cropland extent maps at high spatial resolution are difficult to produce without the relevant training. Despite the potential inherent in RS-based monitoring systems, basic training of scheme managers and extension officers is required for robust output interpretation and analysis. This is especially crucial in accounting for small yet contiguous patches of irrigated areas from dug-wells and dug-outs.

Figure 3 shows the distribution of various sensor applications in the study area. Only 1 journal paper, representing 7% of the total of 12 reviewed, used MODIS, and only 2 journal papers (15%) used ASTER images for mapping agriculture activities in the study area. In addition, only 1 paper (8%) used Sentinel-2 data for cropland extents and irrigation mapping. The remaining studies mapped agricultural activities in the study area using Landsat images (38%). Out of the studies that were discovered on the use of Landsat, only

2% used Landsat 8 ORS-OLI images for LULC mapping in the study area. The enhanced capabilities of Landsat 8 have not been utilized for livestock and agricultural monitoring in the CR-MFS regions of Ghana's Northern Savannah Regions.

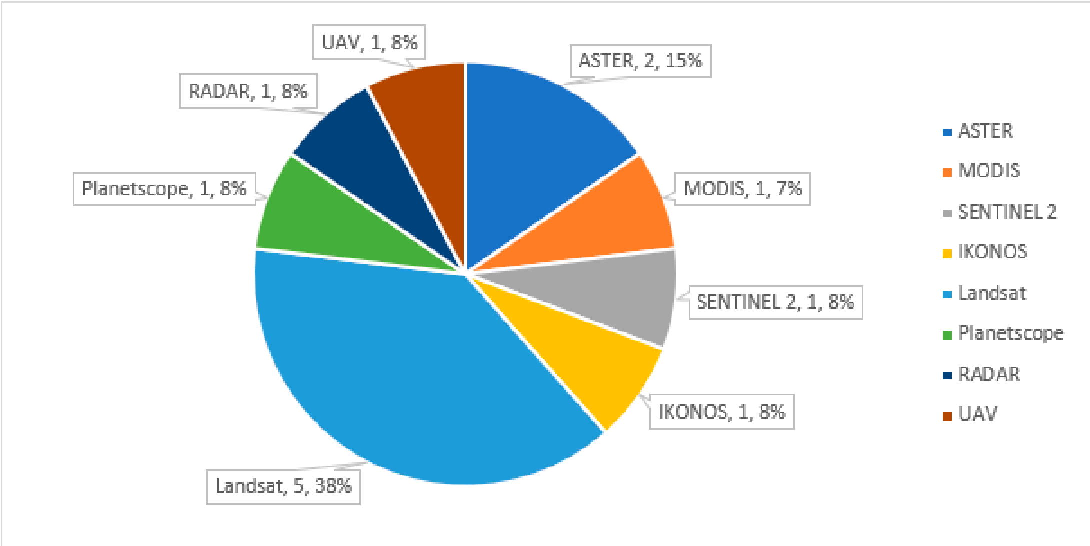

Figure 3. A pie chart showing the remote sensing sensor used in the study area.

Even though sentinel data is equally available and free, agriculture management in the study area has not made use of these data's enhanced spatial resolution. Concurrently, an abundance of sentinel satellite data encompassing the entirety of northern Ghana has been collected since 2013. Sentinel 2 data over the Northern Regions of Ghana is revisited every ten days, enabling near-real-time monitoring of farm animal management, pasture growth, crop performance, and water availability. Consequently, it was discovered that 8% of journal papers integrated macroeconomic information—such as policy and fiscal incentives—with LULC mapping to comprehend the causal relationship between agricultural expansion, yield, and environmental implications.

With reference to the published literature, RADAR and LiDAR have been used in other countries to monitor agricultural phenology, invasive species, soil moisture, field subsidence, and flooding. Examples include the works of Liu et al. [38], Steele-Dunne et al. [45], and Sivasankar et al. [48]. While Figure 3 shows that in CR-MFS areas of Ghana, the use of LiDAR data for farm monitoring and management is lacking, RADAR is only used in one (1) instance. Meanwhile, RADAR and LiDAR data are useful in mapping and monitoring species invasion, cattle movement, soil moisture, and land subsidence [48]. These are the dominant challenges of sustainable agriculture in the study area. Although there are few useful applications for RADAR and LiDAR data, the study area lacks the level of accuracy needed for precision agriculture, rangeland planning and stocking, soil moisture, and nutrient depletion monitoring [55]. As per the 17 Agenda 2030 Sustainable Development targets (SDGs) of the UN, these are necessary to achieve targets 2 (Zero Hunger), 6 (Sustainable Management of Water and Sanitation), and 12 (Sustainable Consumption and Production). Compared to optical imaging, RADAR imagery lacks rich information, which can cause misclassification and the absence of significant agricultural details. This is the primary challenge with RADAR imagery. Nonetheless, reliable data can be obtained by combining RADAR, optical imagery, and digital elevation models (DEM) [18].

The majority of agricultural economies in the Global North have realized how useful unmanned aerial vehicles (UAVs) are for gathering data on farmland, including missing or strayed livestock, flooding, weed and pest invasion, crop health, water and soil contamination, invasive species, herd trajectory monitoring, and the application of fertilizer, weedicide, and insecticide across large farmlands [60,63,109,110]. However, only a single report has been found on the applications of UAVs to irrigation scheme monitoring in the study area (Figure 3). UAVs offer near-real and high-resolution views of farmlands, pasture vigor, irrigation plans, and smallholder reservoirs and are critical for efficient agricultural and animal management, particularly as most peasant farms are smaller than 10 acres in Ghana's northern regions. Thus, there is a lack of usage of UAVs for precision farming, crop management, and animal management, which precludes attempts at addressing food security issues and Goal 2 of the UN SDGs. In this region, large-scale farmers still spray fields by hand, look for stray animals, and apply fertilizer. Thus, it is still difficult to implement sustainable land management techniques. The use of UAVs in precision farming and sustainable land management is imminent and inevitable, even though they are complex technologies that are out of reach for impoverished farmers due to the expense and training involved in acquiring and using them [60,63]. This is presently absent in the study area.

Where UAVs are inaccessible for robust farmland data capture, analysis, and management, very high-resolution satellite data may suffice [111,112]. Therefore, it is feasible to distinguish minute differences in crop performance, soil moisture content, and native and invasive grass species thanks to extremely high-resolution data. In this study, about 8% of the studies used Planetscope, a 3m resolution satellite image. The study mapped the characteristics of Africa's smallholder-dominated croplands, including the sizes and numbers of fields, and provided critical data on food security and a range of other socioeconomic and environmental concerns. Also, 8% of the studies reviewed used RADAR, and 15% used ASTER, respectively. Only one technical report accounted for the socio-economic impact and acceptance study of drone-applied pesticide on maize in Ghana. The study, however, did not capture images with the drone for mapping or monitoring purposes but for pesticide application, which is part of precision farming. Planetscope data are commercial, and only few a funded projects encourage the use of these data. However, because of restricted funding for funded initiatives, CR-MFS areas in Ghana's Northern Regions do not have access to very high-resolution satellite images for managing and making decisions in farming, as well as the effects on the environment.

Field Observations and Key Findings

Robust primary data collection was achieved using focus group discussions (FGD) and ground truthing. Specifically, FGD in conjunction with participatory rural evaluation approaches, aids scientists in producing pertinent primary data [113,114]. Some of the findings from the literature were confirmed by field observations. These results were cross-validated by community members (Figure 4).

Figure 4. Emergence of a Natural Dam at Karaga in the Northern Region.

On farmlands, new grass species known as "Burkina" (Figure 5) have been observed by farmers. In most farming communities, the "Burkina" grasses are thought to be the cause of the depletion of water retention capacity and soil nutrients.

Figure 5. (**a**–**c**) "Burkina" Invasive Grass Species, which dominates most farmlands in the Northern Region.

The usage of fertilizers on farmlands and weedicides like "condemn" are thought to be the causes of the "Burkina". Throughout the previous five years, the research region would have been able to map and observe the emergence of "Burkina" if high-resolution RS data had been applied. There were variations in the spectral fingerprints when compared to cropland cover data from the same area during a three-decade timeframe. There have been significant changes in agricultural extents and smallholder water reservoir availability when comparing photos of farmland cover from five years ago with more recent image analysis. It is a typical case that calls for continuous and frequent farmland surveillance in the research region. In other places, gullies and gutters turned into sizable sections of streams in just three (3) seasons. Therefore, in order to demonstrate a relationship between farmlands, pasturelands, and urbanization, a baseline spatial analysis of developments in the majority of communities is required. As a result, the field observations also demonstrated the necessity of doing frequent fieldwork to close knowledge gaps on the dynamics of resilience and sustainable land management in the region. For example, streams and drains have arisen on farmlands in Dangi, Sissala East District, Upper West Region, preventing access to farmlands. Certain farmlands become impassable during the height of the rainy season. According to reports, these advances escaped early detection and appeared in Dangi within the previous two years.

5. Conclusions

This paper uses a systematic literature review and field observations to explore the applications of RS data in enhancing sustainable and precision agriculture in CR–MFS areas in the Northern Savannah Regions of Ghana. The literature review explored both published and grey literature on the application of RS for mapping the extents of cropland, pastureland, smallholder water, and irrigation area mapping over a thirty (30) year period (1992–2022). Field observations were conducted to validate the findings from the literature survey. In spite of the advantages of RS in enhancing precision agriculture in many places, its adoption and use in many developing countries, such as Ghana, is slow and dearth in many instances. Our fieldwork investigations show that both peasant and commercial farmers in the CR-MFS areas in the Northern Savannah Regions of Ghana have yet to adopt RS for precision farming. Thus, most farmers in the study area do not have the technology to benefit from all the advantages it comes with, including management plans. To begin with, assisting farmers with RS technologies on monitoring to prevent yield losses from weeds, insects, and diseases may provide the most economic and environmental benefits. Also, access to timely, cost-effective RS data and integrating these with decision-derived value-added products, decision support systems, or other expert systems in a user-friendly fashion are needed in the study area. However, the costs of high-resolution satellite data acquisition need to be subsidized. To subsidize, such a cost would necessitate the deployment of UAVs to assist farmers with precision agriculture.

New developments in UAVs and sensors facilitate cost-effective data collection at very high spatial and spectral resolutions. The use of UAVs in precision farming and sustainable land management is currently lacking in the area. However, although satellites are capable of mapping large areas at an instance, UAVs are most suitable at the farm-by-farm level rather than regional-scale level mapping. The loss of certain native species of grass, the emergence of new species, waterlogging, and the appearance of natural dams and streams in some areas were validated during field observations. With the application of very high-resolution RS data, early warning signs could have been detected and mitigation measures taken. In the study area, only one study used RS data to report on farmland performance and soil moisture indices. It is critical for comprehending the possible causes of nutritional depletion that are not typically discussed in the literature. Currently, it is unknown whether CR–MFS have negative impacts on soil water retention and invasive species occurrences. If there are any such negative impacts, they have not been detected.

6. Recommendation

By incorporating UAVs into research and management strategies, stakeholders can delve deeper into understanding the complexities of crop performance, soil moisture variations, and the nuanced distinctions between native and invasive species of grasses. Furthermore, recognizing the significance of UAVs in monitoring land degradation and related phenomena necessitates a call for increased funding and investment in this domain. Investment will not only accelerate technological advancements in UAV capabilities but will also facilitate the widespread integration of UAVs into monitoring programs, ensuring sustainable and informed decision-making in agricultural practices. This effort will not only advance scientific understanding but also pave the way towards enhancing sustainable and precise agriculture, informed farmer decisions, and sustainable land use practices in the study area. Noteworthy, however, is the fact that UAVs are only capable of mapping at the smaller unit farm-by-farm level and not at the regional land use classification level.

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