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Review

A Review: Potential of Earth Observation (EO) for Mapping Small-Scale Agriculture and Cropping Systems in West Africa

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Abstract: West Africa faces a complex range of challenges arising from climatic, social, economic, and ecological factors, which pose significant risks. The rapidly growing population, coupled with persistently low agricultural yield, further exacerbates these risks. A state-of-the-art monitoring and data derivation of agricultural systems are crucial for improving livelihoods and enhancing food security. Despite smallholder farming systems accounting for 80% of cultivated cropland area and providing about 42% of the total employment in West Africa, there exists a lack of a comprehensive overview of Remote Sensing (RS) products and studies specifically tailored to smallholder farming systems, which this review aims to address. Through a systematic literature review comprising 163 SCI papers sourced from the Web of Science database (Filter I), followed by a full-text review (Filter II), we analyze the RS sensors, spatiotemporal distribution, temporal scales, the crop types examined, and thematic foci employed in existing research. Our findings highlight the predominance of high to very high-resolution, multispectral sensors as the primary data source and we observe that a wide array of available sensors and datasets, along with increasing computing capacities, have shaped the field over the last years. By highlighting existing knowledge, this study identifies the potential of RS and pinpoints the key research gaps. This sets the stage for future investigations aimed at addressing critical challenges in West African smallholder agricultural systems.

Keywords: Africa; West Africa; review; remote sensing; earth observation; agriculture; farming; food security; monitoring; sustainable intensification

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1. Introduction

1.1. Small-Scale Agriculture in the Context of Global Change

Food security is one of the world's most pressing challenges in the face of a continuously increasing world population, and even more so as climate change puts more pressure on the natural resources we depend on [1]. As of 2023, approximately 733 million people worldwide are chronically undernourished, including 298 million in Africa, with 33.1 million in West Africa [2]. In West Africa, smallholder farmers cultivate > 80% of the cropland, employing about 42% of the labor force [3–6]. Smallholders are defined as small-scale farmers who manage areas from less than 1 ha up to 10 ha and are characterized by family-focused motives such as favoring the stability of the farm household system, using mainly family labor for production, and using part of the yields for family consumption [6]. Their limited resources and rainfall-dependent farming practices make them highly sensitive to the effects of climate change [7]. Among the regions where smallholder farming is predominant, West Africa is considered one of the most important because of its geographical size and the potential for yield growth in the coming decades [4]. However, the large increase in population urgently demands enhanced production and improvements in the governance of food production systems. These improvements are also a prerequisite for achieving the United Nations (UN) Sustainable Development Goals (SDG). Food security plays a prominent role in SDG2 "Zero Hunger" as well as SDG1, as the agriculture and food sector is key to eliminating poverty for many people [1,8]. More specifically, SDG target 2.3 aims to double the agricultural productivity and the incomes of small-scale food producers by 2030, in particular for women, indigenous peoples, and family farmers [8]. Smallholder systems are characterized by large yield gaps [9,10], which arise from the numerous challenges they face. These challenges include their small plot size, often less than 1 ha, environmental variability, low soil fertility, mixed cropping systems, and suboptimal practices. These obstacles continue to impede sustainable improvements in agricultural productivity and quality [11–14]. As a result, a large proportion of these households are themselves food insecure and fall below the poverty line. The probability of smallholders escaping poverty depends directly on their ability to increase the productivity of their crops [5,15]. These constraints may be reduced through integrated soil fertility management (ISFM), improved crop–livestock integration, multi-purpose crops, and various other sustainable intensification (SI) practices [10,16,17]. Previous research showed that small-scale irrigation can play a pivotal role in agricultural production, reduce farmer reliance on the varying rainfall patterns that characterize the climatic conditions of sub-Sahara Africa, facilitate economic transactions, and improve community livelihood, wealth, and infrastructure [18,19]. However, these solutions must consider a dynamic socio-economic and climatic context, where evolving urban demand, market access, IT dissemination, and social differentiation present both risks and opportunities [11,16,20,21].

As the challenges of ensuring food security and sustainable agricultural practices become more complex there is a need for precise, data-driven solutions. Remote Sensing (RS) offers a powerful opportunity for monitoring, assessing, and optimizing agricultural activities across the heterogenous landscape of West Africa [1,12,18,22,23] as an increase in agricultural productivity is imperative [24–26].

1.2. Remote Sensing Perspective

RS techniques are widely used in agriculture and agronomy [27–30]. The monitoring and mapping of agricultural systems benefit particularly from RS due to specific challenges not common in other sectors [27,31]. Agricultural production follows strong seasonal patterns related to the phenology of crops. The production depends on heterogenous environmental factors such as soil type and properties, climatic-driven variables, and agricultural management practices, all of which are highly fluctuative in time and space. RS can contribute considerably to providing a timely and accurate perspective of the agricultural sector, as it gathers information over large areas with high revisit frequency [27,29,32]. Various techniques for gathering this information, such as imaging spectroscopy, fluorescence spectroscopy, and thermal and microwave RS, provide different insights into agricultural systems [28,33,34]. RS offers physical measurements of crop areas, capturing their temporal and spatial development. This approach indirectly integrates key factors influencing crop productivity [35], such as sowing dates [36], pest infestations [37], irrigation practices [19], and levels of intensification [38], that are challenging to access or too costly to measure directly [33]. For example, satellite data can be particularly useful for assessing the extent of irrigation and identifying irrigated cropland over time. This information is crucial for mitigating the impacts of extreme weather and climate variability [19,39].

Optical data, which depend on weather conditions, are particularly affected by cloud cover and therefore, may be less effective, especially in southern West Africa. Very high-resolution commercial satellites, such as IKONOS, QuickBird, WorldView, Planet, etc., can capture small fields with greater detail, but their high costs restrict their use in small-scale studies and limit their application for large assessments [40–42]. Instead, high-to-moderate-resolution satellite imagery such as from the Landsat and Sentinel missions, are generally more suitable for larger-scale studies. Landsat provides a long-term, multi-decadal record of moderate-resolution images (30 m), making it useful for tracking changes in arable land over time. In contrast, Sentinel-2, launched in 2015, provides higher spatial resolution (10–20 m compared to 30 m), higher return frequency (5 days versus Landsat's 16 days), and additional narrow bands in the red-edge and near-infrared regions. These features help to detect finer changes in crop status and improve the accuracy of mapping agricultural systems [29,32]. Sentinel-1 Synthetic-aperture Radar (SAR) data, available since 2014, complements optical data by providing consistent measurements that are almost unaffected by cloud cover. This is particularly valuable for monitoring small fields in cloud-covered areas of West Africa. For example, Sentinel-1's SAR sensor offers detailed information on crop canopies and moisture status, which, when combined with Sentinel-2, enhances the ability to distinguish between different crop and land cover types [29,32]. Open data archives such as those of Landsat, MODIS (Moderate-resolution Imaging Spectroradiometer), or the Sentinel fleet enable research on all geographical scales from local to global at high temporal and spatial resolution [43,44]. MODIS sensors offer data more continuously due to their high temporal resolution and their globally uniform acquisition scheme, but the spatial resolution of 250 m or less is not satisfactory to delimit small-scale agricultural areas [43,45]. However, the growing trend towards sensor constellations is overcoming this limitation, a trend also evident in the development of high-resolution commercial satellite constellations [43].

Additionally, integrating various data sources can overcome individual limitations and improve mapping accuracy, especially in regions with variable weather conditions. The inclusion of other data sources, such as GEDI or UAV data further expands the potential of RS for mapping smallholder agriculture and cropping systems in West Africa [22,46]. The need for improvements in cropland area assessment in this region, coupled with the potential for improvements made possible by using higher resolution data, also increases the need for computational resources, new methods, and technical skills for effective processing and analyses [47]. Recent studies have supported the hypothesis that data fusion can improve crop mapping [48,49]. The success of RS applications hinges on both the quality of the data and the analytical techniques used. Machine learning (ML) offers a range of techniques, including conventional models like Random Forest, Support Vector Machine, Decision Trees, and k-nearest neighbors. In contrast, Deep Learning is a specialized subset of ML that focuses on models like (convolutional) neural networks (CNN) and multi-layer neural networks for effectively analyzing big datasets and complex tasks [40,50].

1.3. Structure and Objectives of This Review

As the above information shows, food security in West Africa is increasingly threatened by rapid population growth, low agricultural productivity, and the impacts of climate change. Smallholder farmers, in particular, face substantial challenges due to limited resources and their reliance on rainfall. RS technologies offer a promising solution to address these challenges, providing valuable data for improving agricultural monitoring, enhancing productivity, and supporting sustainable practices in the region. This review aims to provide a comprehensive overview of RS products and studies focused on smallholder farming systems, assessing the potential of Earth Observation (EO) for mapping small-scale agriculture and cropping systems in West Africa. We analyzed 163 scientific papers published between 1 January 2000 and 30 April 2024, with the overall structure of the review outlined below:

- The introduction in Section 1 presents the relevance of the potential of RS to monitor and map agricultural and cropping systems in West Africa amid increasing and multidimensional challenges of global change.
- Section 2 first provides a geographical overview of the study area and secondly explains the literature selection process by providing an overview of the literature databases used and the filters applied.
- Section 3 presents the results of the review process. It aims to identify the potential of EO for mapping small-scale agriculture and cropping systems in West Africa. First, the evolution of the research field over time is described. This is followed by a detailed spatial breakdown based on the affiliation of the first authors, the origin of the study funding and the location of the study area. The sensors used and the temporal and spatial scales are presented in the next subsection. Section 3 concludes with an in-depth analysis of the research foci. The classified studies are analyzed on their main findings, RS potential and their challenges and limitations in order to identify relevant research gaps.
- The discussion of the results, the limitations of the review, the need for integrating high-resolution RS data and future research directions are presented in Section 4.
- Section 5 highlights the main findings, and concludes with the potential of RS to detect the impacts of global change in West Africa and how RS can support sustainable intensification.

2. Materials and Methods

2.1. Study Area—West Africa

The area of interest for this literature review is West Africa as defined by the United Nations (UN) in the M49 standard [51], comprising the following countries: Benin, Burkina Faso, Cabo Verde, Côte d'Ivoire, Gambia, Ghana, Guinea, Guinea-Bissau, Liberia, Mali, Mauretania, Niger, Nigeria, Saint Helena, Senegal, Sierra Leone, and Togo. Covering approximately one quarter of Africa, West Africa contains a broad range of ecosystems, bioclimatic regions and habitats from rainforest to desert. From the arid Sahara in the north to the humid southern coast, five distinguishable broad east–west belts characterize the West African climate and vegetation [52] (Figure 1a,b).

Figure 1 shows the terrestrial ecoregions delineated based on the biogeographic distribution of species, communities, and endemic genera by Olson et al. [53]. Rainfall levels and temperature also can be used [52,54] to derive gross biophysiological features resulting in the Saharan, Sahelian, Sudanian, Guinean, and Gunieo-Congolian regions. The Sahara Desert stretches across the whole north extent of West Africa. It is characterized by arid landscapes, dune fields, gravel plains, and rugged mountains. Average annual rainfall ranges from 0 to 150 mm per year. The Sahel is a broad semiarid belt averaging about 350 km wide. Climatically it is characterized by an average rainfall of between 150 and 600 mm, with great variability of amount and timing in a given year, and by a dry season lasting 8 to 9 months (Figure 1). It is also home to countless small wetlands as well as large water features including the Senegal River, the Inland Niger Delta, and the Lake Chad Area. It transitions in the south to the Sudanian Region, which is the domain of savanna, ranging from open tree to wooded savannas and to open woodlands. Annual rainfall is between 600 and 1200 mm and the dry season lasts 5 to 7 months. Further south, the Guinean Region is generally defined by an average annual rainfall of between 1200 and 2200 mm and is the domain of seasonally wet-and-dry deciduous forests. Canopy cover is dense and closed with tree heights averaging 18 to 20 m. It has a distinct dry season of 7 to

8 months, which distinguishes it from the Guineo-Congolian Region. This is the wettest in West Africa with 2200 to 5000 mm annual rainfall. Here, there are two rainy seasons, one long and a short one interrupted by short, drier periods [52,53,55]. The rainfall and temperature patterns are illustrated in Figure 1c, using climate diagrams that present the average temperature and precipitation data from 1991 to 2020. These graphs span from northern to southern regions, showcasing Mauretania and Niger as representative of the Sahel zone, Senegal for the Sudanian region, and Ghana and Sierra Leone as a blend of the Guinean and the Guineo-Congolian zone. Sierra Leone exhibits notably high precipitation amounts characteristic of the Guineo-Congolian zone, while also displaying the distinct dry season of the Guinea region, reflecting national averages. Southern Ghana lacks the extended dry season, instead exhibiting a shorter one, alongside two rainy season peaks.

The diversity of bioclimatic zones across West Africa influences the land use and therefore, the types of crops cultivated in the region. Each zone provides distinct environmental conditions that support specific crops, leading to a variety of cropping systems and agricultural outputs essential for both domestic consumption and export. Major staple crops include maize, millet, sorghum, rice as well as groundnut, cassava, and yams [2,53,54]. Millet, for instance, is widely grown due to its adaptability to semi-arid conditions, where other crops often require irrigation, and its high nutritional value [55]. Groundnut is a key crop in several countries, including Nigeria, Mali, Côte d'Ivoire, Burkina Faso, Ghana, and Senegal [54]. Similarly, cotton serves as an important cash crop in areas such as Mali, Nigeria, Benin, Togo, Côte d'Ivoire, and Burkina Faso [56–58], significantly impacting local livelihoods. In contrast, the Upper Guinean forests, particularly in Ghana and Côte d'Ivoire, are renowned for cocoa production, which engages approximately two million farmers throughout West Africa. This diversity of crops across various regions highlights the distinct agricultural practices shaped by local environmental conditions [59–61].

Agriculture is not only central to West Africa's economy but also to its demographic makeup. Population characteristics such as rural and urban distribution, labor force participation, and dependency ratios, illustrate the critical relationship between the region's people and their agricultural livelihoods. According to the UN [26], 441 million people live in West Africa, 43% of which work in the agricultural sector. This marks a substantial decline from the year 2000, when 75% of the population was engaged in agriculture (Figure 1d,e). The median age in West Africa is 18, highlighting a young population that will continue to shape agricultural practices and labor availability [26]. While crop types vary across bioclimatic zones, farm size also plays a crucial role in determining agricultural productivity. Understanding the average farm size across the region sheds light on the scale of operations and the challenges that farmers face in different areas. Despite the large number of individuals engaged in agriculture, productivity levels vary widely, often due to disparities in farm size, access to resources, and the efficiency of agricultural techniques. For instance, Ghana serves as a representative case for West Africa, with small-scale farms averaging 1.56 hectares and a national average of 2.56 hectares [58]. These differences highlight the diverse farming structures and operational challenges across the region.

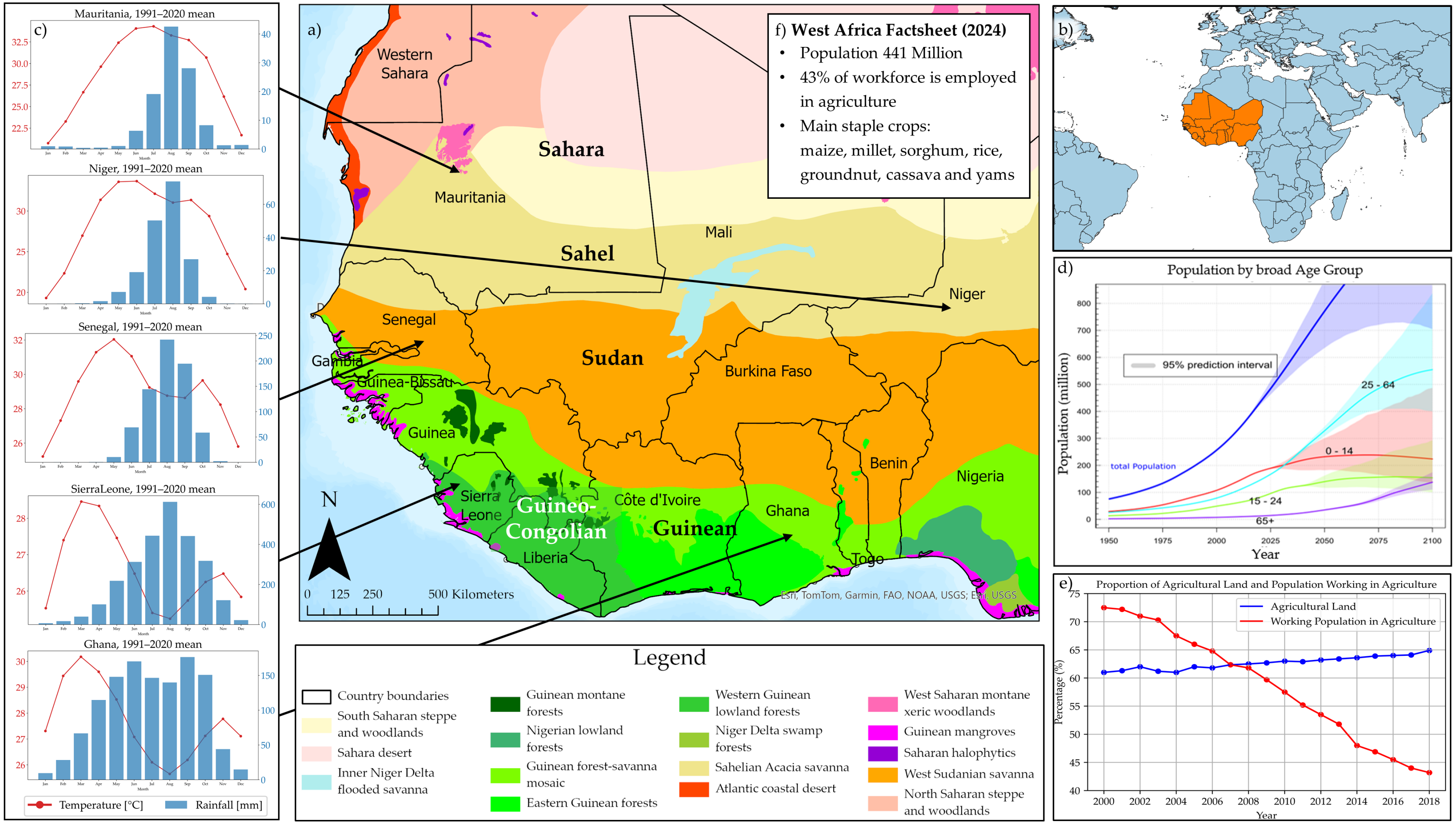

Figure 1. Overview of the study area. (**a**) Displays the terrestrial ecosystems by Olson et al. [53] and the bioclimatic zones, (**b**) is the localization map of the study area based on USGS [52], (**c**) climate graphs of Mauretania, Niger, Senegal, Sierra Leone, and Ghana averaged from 1991 to 2020 and over the area of each country; based on WorldBank Climate Change Knowledge Portal [56], (**d**) total population and population by age group based on UN World Population Prospects [26], (**e**) shares of agricultural land and population working in agriculture based on FAO STAT [57], and (**f**) fact sheet on West Africa based on UN World Population Prospects and FAO STAT [26,57].

2.2. Review Process

A structured literature search on the potential of EO for mapping small-scale agriculture and cropping systems in West Africa has been conducted using the Web of Science (WoS) platform (last accessed 1 May 2024). The platform enables an in-depth literature search on the basis of search strings and additional filter criteria such as language, discipline or publication year. We employed conditional statements to ensure the studies addressed each of the three topics: Remote Sensing, West Africa, and Small-Scale Agriculture. To allow some leeway, several synonymous search terms for each topic were employed (Table 1).

Table 1. Criteria entered in the WoS search string. The asterisk (*) represents any group of characters, including their absence.

Criteria	Conditions
Remote Sensing and Earth Observation	"remotely sensed" OR "remote sensing" OR "earth observation*" OR "satellite" OR "IKONOS" OR "Quickbird" OR "WorldView" OR "Pleiades" OR "Rapideye" OR "GeoEye" OR "Planet" OR "skycat" OR "SPOT 4" OR "SPOT 5" OR "SPOT 6" OR "SPOT 7" OR "SPOT-Vegetation" OR "Landsat" OR "Sentinel" OR "AVHRR" OR "MODIS" OR "Envisat" OR "Aster" OR "ALOS" OR "TanDEM-X" OR "TerraSAR-X" OR "DESIS" OR "PRISMA" OR "EnMAP" OR "Hyperion" OR "GEDI" OR "optical imagery" OR "optical satellite" OR "Synthetic Aperture Radar" OR "Radar" OR "RadarSat" OR "COSMO" OR "SRTM" OR "microwave satellite" OR "multispectral satellite" OR "hyperspectral satellite" OR "imaging spectroscopy" OR "thermal satellite" OR "airborne laser scanning" OR "unmanned aerial vehicle*" OR "NDVI"
West Africa	"ECOWAS" OR "West* Africa*" OR "Togo" OR "Benin", OR "Ghana" OR "Ivory Coast" OR "Côte d'Ivoire" OR "Burkina Faso" OR "Cape Verde" OR "Gambia" OR "Guinea" OR "Guinea-Bissau" OR "Liberia" OR "Mali" OR "Mauritania" OR "Niger" OR "Nigeria" OR "Senegal" OR "Sierra Leone" OR "Saint Helena" OR "Ascension" OR "Tristan da Cunha"
Small-Scale Agriculture and Cropping Systems	"agri*" OR "agriculture" OR "crop*" OR "farm*" OR "cowpea" OR "groundnut" OR "maize" OR "sorghum" OR "soy*" OR "yams" OR "shea*" OR "cassava" OR "cocoa" OR "rice" OR "corn" OR "cotton" OR "millet" OR "palm*" OR "peanut" OR "cashew" OR "above*ground biomass" OR "vegetation productivity" OR "intercropping"
Language	English
Document Type	Article
Date	1 January 2000–30 April 2024

This search string was applied to the 'topic' (TS) term, which returns results based on title, abstract, and keywords. First, we looked for studies that incorporate RS using a list of commonly used sensors and EO terms. The second search element was concerned with geographical terms defining the study area of West Africa. Third, the search terms for the small-scale agricultural systems are set. Terms like "agri*" were selected to comprehensively cover various crops and agricultural practices relevant to West Africa. It should be noted that the keyword "field*" was excluded as it yielded only a few additional relevant articles that could be captured through other keywords during the search string development, while predominantly introducing articles with a divergent focus. Similarly, the keyword "small*scale" did not return additional studies and was therefore excluded from the search string. The search is limited to English papers, classified as "articles" document types that were published between 01.01.2000 and 30.04.2024. This confirms that the publications considered have undergone peer review and are both comprehensive and current, providing a thorough overview of the literature on small-scale agriculture in the region. The year 2000 aligns with the launch of MODIS [59], a major EO mission, which began providing critical data, and with the rapid increase in related scientific publications accelerated by opening vast archives, such as Landsat's data repository in 2008 [60].

Figure 2 depicts the workflow, which involves two filters after the initial WoS result with n = 853 publications. In the first step, we scanned the results by title and abstract and only included publications with a clear focus on RS and agriculture. Land use and land use change (LULUC) studies were only included if they have a crop-specific focus, e.g., mapping maize cropland in northern Nigeria [61,62]. All aquaculture, mangrove, and urban studies were excluded. Publications analyzing forests were excluded, except studies on agroforestry, e.g., cocoa. This first filter resulted in n = 260 publications, which were fully read in the next filtering step and then further reduced to a total of n = 163 relevant articles for this review topic (Figure 2).

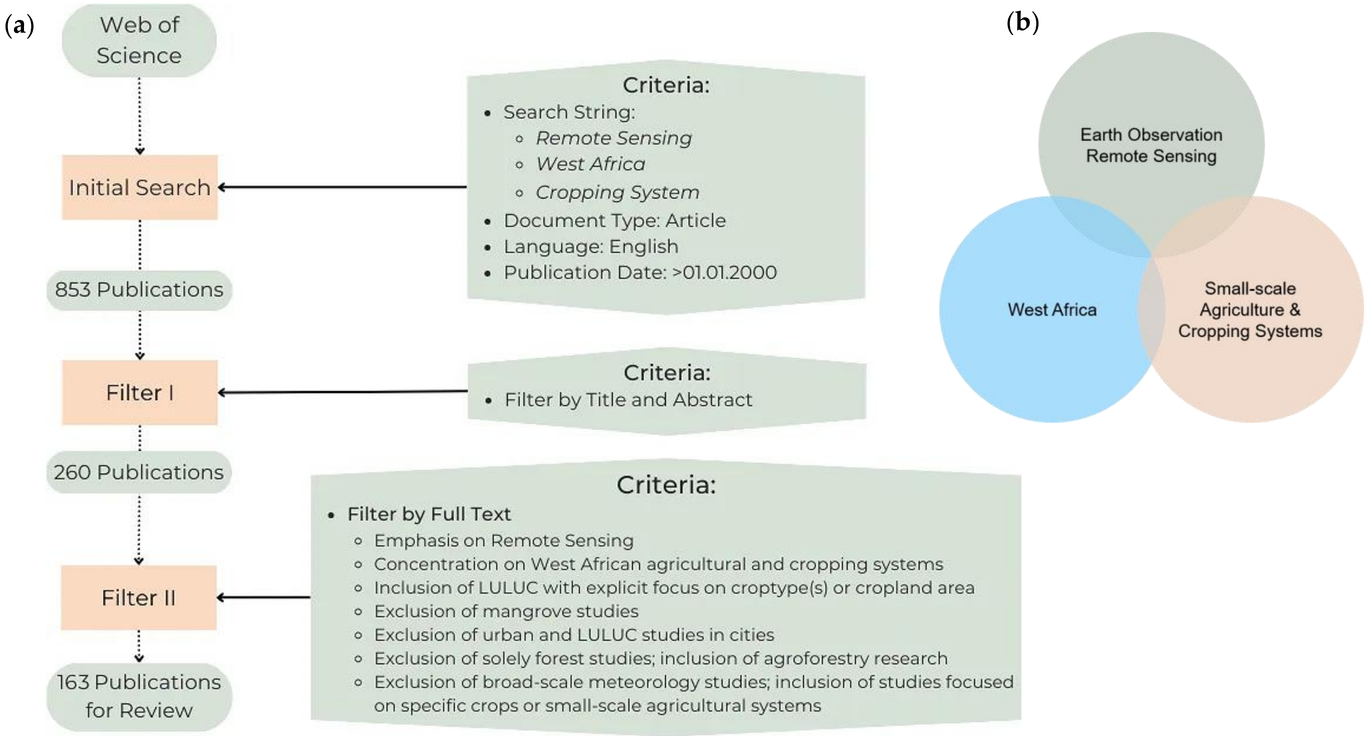

Figure 2. (**a**) Workflow chart outlining the literature search process used to identify n = 163 relevant scientific articles about the potential of RS for mapping small-scale agriculture and cropping systems in West Africa. (**b**) Outline of the Web of Science "topic" search.

3. Results

The following section presents the main findings of the reviewed articles on the potential of EO for mapping small-scale agriculture and cropping systems in West Africa:

- First, the distribution of publications in different journal categories over time is shown in Section 3.1.
- In Section 3.2., the publications are subdivided spatially, both with regard to the affiliation of the first author, the origin of the funding and with regard to the study area.
- The analysis of the sensor name and sensor type, as well as their carrier system, is presented in Section 3.3.
- In Section 3.4, the spatial and temporal resolutions, as well as the different study periods, are analyzed in detail.
- This is followed by an in-depth examination of the crops of interest in Section 3.5, including the comparison of the crops represented in the studies versus their contribution to the overall agricultural economic value and their proportion of agricultural land.

- Subsequently, in Section 3.6, an in-depth analysis of the thematic foci of the respective studies is presented in order to identify conclusive research gaps.

3.1. Development of Research Interest over Time

The development of the research field can be assessed by the number of publications over time. Composite Figure 3 presents both a bar chart and a donut chart, providing a comprehensive visualization of the annual publication count for each journal category and overall distribution. Four journal categories are selected to classify each publication to a specific group: “Remote Sensing”, “Agronomy”, “Environmental Science”, and “Other”. The category “Other” includes all journals that do not fit into one of the three categories, such as the journals “Global Healthaction”, “Engineering of Applications of Artificial Intelligence”, or “American Journal of Tropical Medicine and Hygiene”.

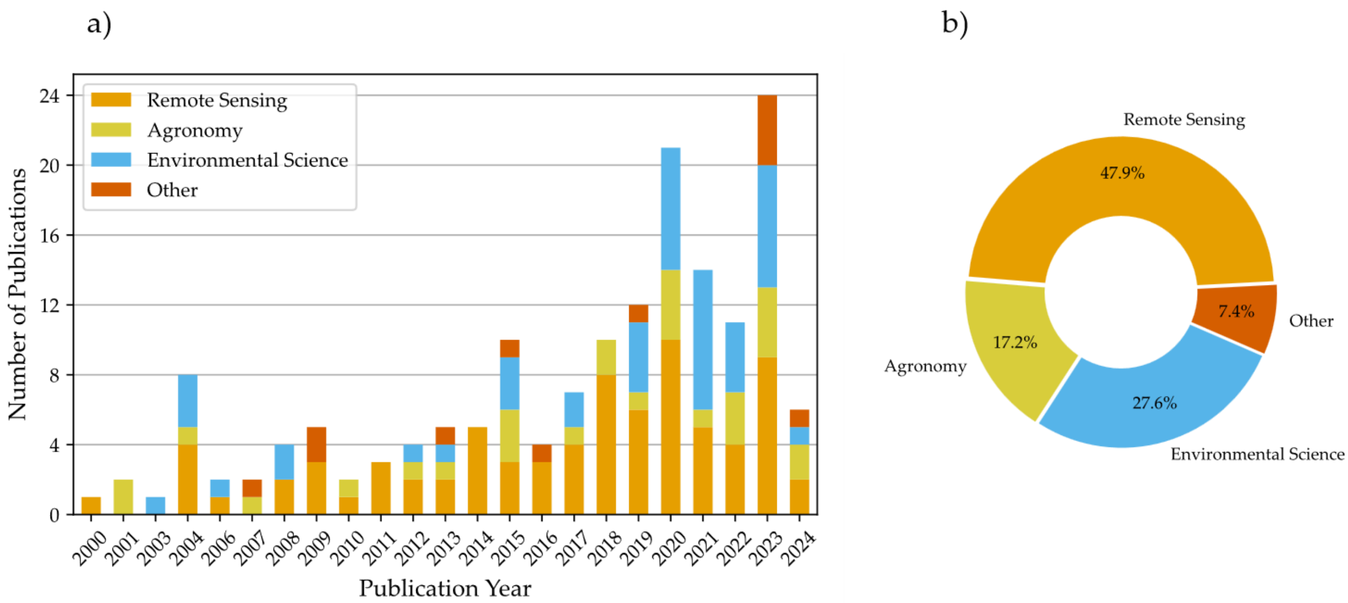

Figure 3. Distribution of publications subdivided into different journal categories: (**a**) temporal and (**b**) overall.

The bar chart on the left side of Figure 3 shows that, as of the end of April 2024, only six publications had been released during the year. This is likely due to the limited time frame. The overall trend depicted in the figure shows a clear increase in the number of publications over time, with 2023 reaching a peak of 24 publications. Notably, 53% of all publications have been released since 2019, highlighting the recent increase in output. “Remote Sensing” stands out as the most frequent category in nearly every year, especially in recent times, reflecting a growing emphasis on this field. Nearly half of the 163 publications (47.9%) fall under this category. “Environmental Science” is also consistently represented, though less frequently than “Remote Sensing”, comprising 27.6% of the total publications. “Agronomy” shows a steady presence, accounting for 17.2% of the publications, with noticeable activity in 2020, 2022, and 2023, suggesting a slight increase in focus on this area recently. In the earlier years (2000 to 2014), there were fewer publications and categories, with “Remote Sensing” still dominant but less frequent overall, followed by an expansion in the later years. Twelve publications (7.4%) could not be classified into any of these categories.

3.2. Spatial Analysis on Affiliations and Study Areas

As shown in Figure 4, France and the United States lead with the most first author affiliated publications, each contributing 25, followed by Germany with 19. Senegal follows next with the most publications of the West African countries (8), alongside with the Netherlands. These five countries already represent over 50% of the studies. Belgium, Nigeria, and Denmark each contribute seven studies, followed by China contributing six articles, more than any other Asian country. There is a wide distribution of countries affiliated with less than five publications.

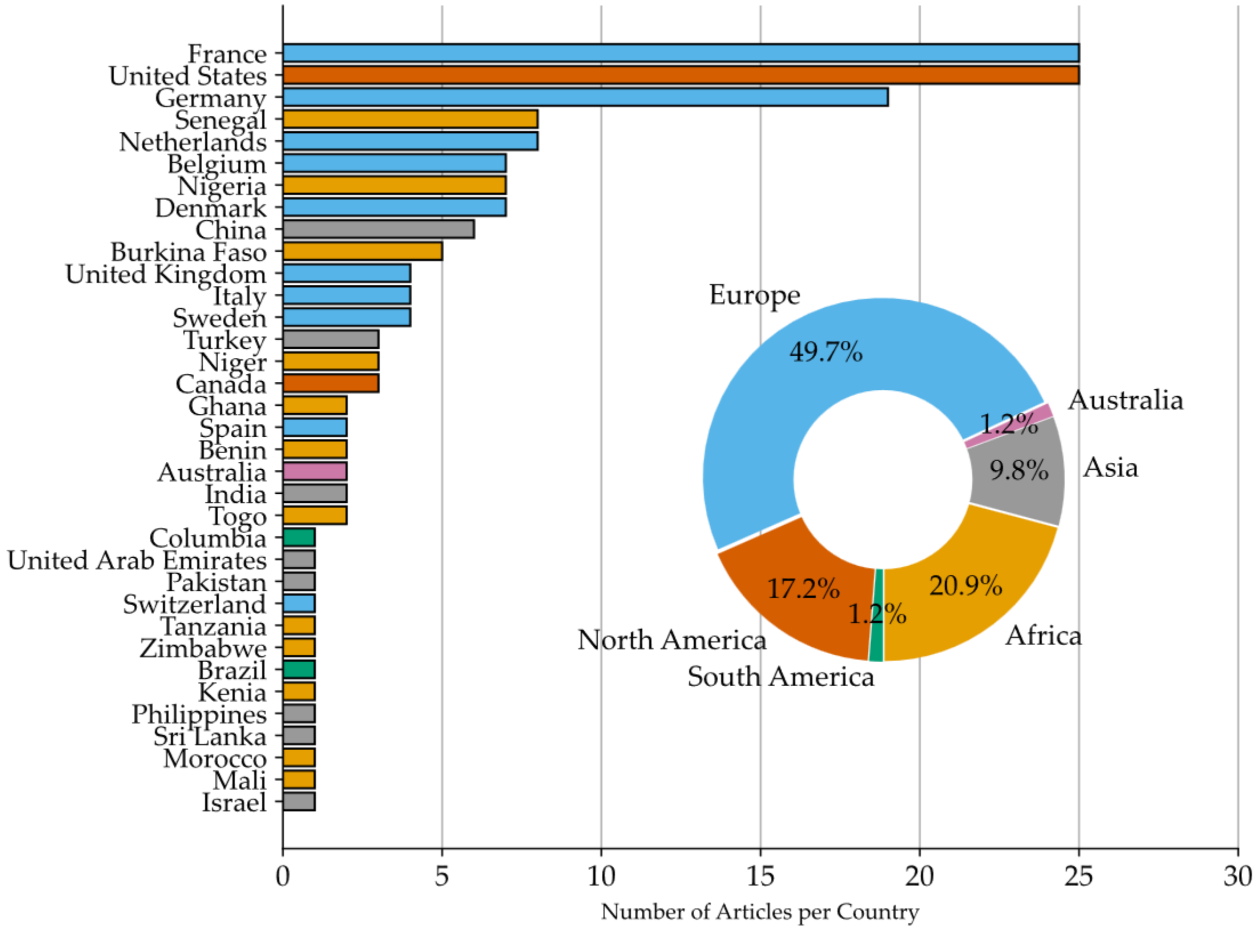

Figure 4. The bar plot displays the first author affiliation by country and by continent in the donut chart.

Europe accounts for almost half of the publication affiliations (49.7%), followed by Africa (20.9%), North America (17.2%), Asia (9.8%), and South America and Australia each contributing two publications. The top West African countries in terms of first author affiliation are Senegal and Nigeria (seven studies) and Burkina Faso with five studies.

One author, G. Forkuor [34,63–66] from WASCAL (West African Science Service Centre on Climate Change and Adapted Land Use) in Burkina Faso and University of Würzburg has five publications. Two authors have four publications: L. Leroux [33,67–69] from CIRAD (French Agricultural Research Centre for International Development), Senegal and E. Vintrou [45,70–72] from CIRAD France. M.A. Diuk-Wasser has three publications [73–75]. All other authors have two or fewer publications.

Figure 5 displays the studied areas. Some studies were conducted in multiple regions rather than in a single country or with a coverage larger than a country area. Those are listed several times. In addition, there are ten studies covering West Africa, which are excluded from this graph for a more concise representation. Most studies have been conducted in Burkina Faso and Senegal (37 each), followed by Mali (32). These three countries constitute over 50% of the reviewed articles. Nigeria (22), Ghana (21), and Niger (19) are also frequently the subject of research. Benin (nine), Mauretania, and Côte d'Ivoire (each have eight) show a moderate level of research interest, with several studies carried out. Gambia, Guinea, and Togo are studied less frequently, whereas Guinea Bissau, Sierra Leone, and Liberia (and St. Helena and Cabo Verde) are not represented in the articles in the context of this review besides the ten studies covering all of West Africa.

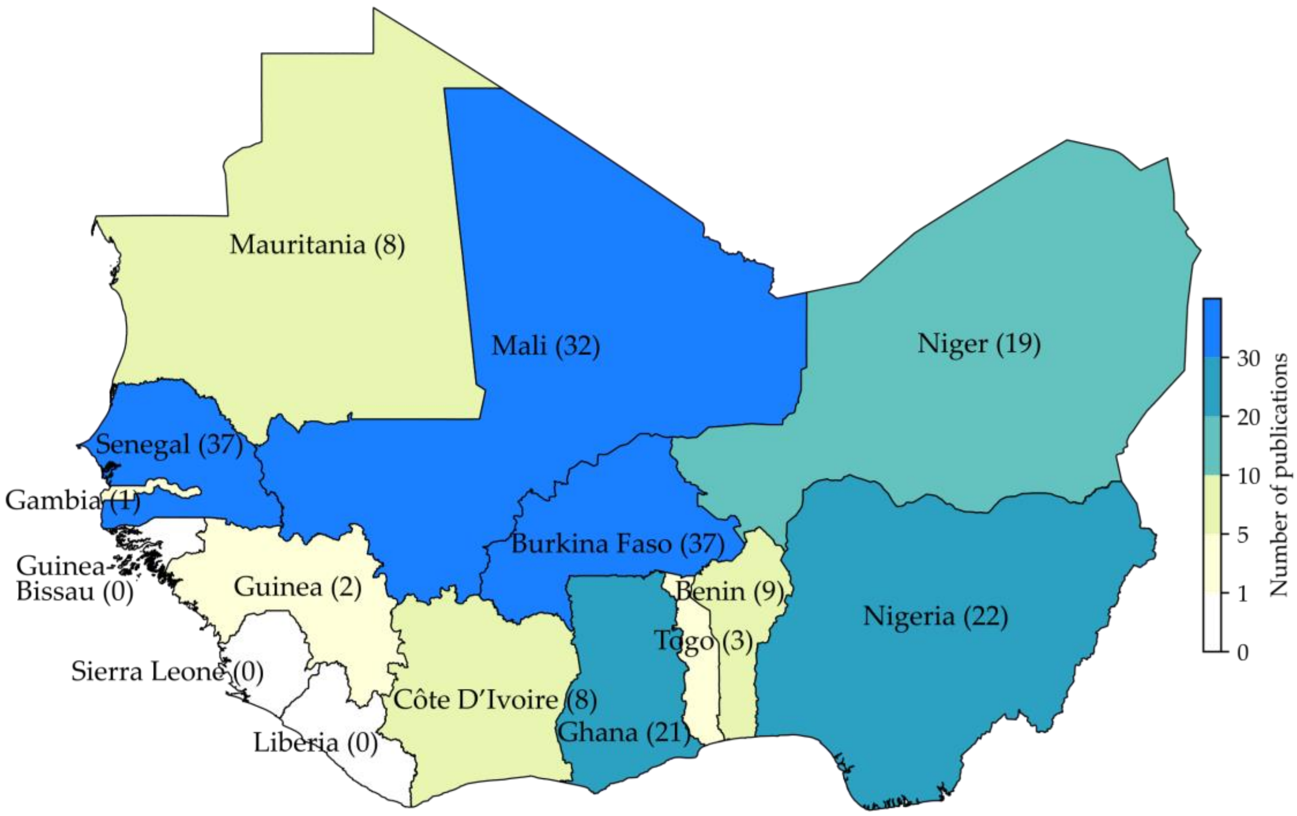

Figure 5. Map showing the spatial distribution of study areas by country, with numbers indicating the exact number of studies conducted in each country. Ten studies covering the entire West Africa region are excluded from this map. Individual studies may be associated with multiple countries.

The origin of a study's funding in relation to the study area is displayed in the Sankey graph in Figure 6. If a publication does not specify a funding source, the first author affiliation is taken as a proxy of the origin of the funding. The majority of the studies indicate a funding source. No distinction is made regarding the type and sources of funding—whether from governmental agency funding programs, NGOs, or private contributions. Only the country of origin is considered relevant. For instance, the "Bill and Melinda Gates Foundation" (BMGF) is categorized as USA funding and the German "German Federal Ministry of Education and Research" (BMBF) is identified as a German funding source. Additionally, there is international funding, in specific for the European Union, as well as one study that is solely financed by WorldBank, which is classified under "Other". In cases of multiple funding sources, the first mentioned source is used for the analysis.

Studies that receive funding from a country represented by only one instance are categorized under "Other", including Pakistan, Saudi Arabia, Australia, Columbia, Japan, Morocco and an international funding solely through WorldBank. The largest share of funding comes from the United States, which accounts for 59 studies. Germany follows with 40 studies. Together, these two countries account for 47% of the studies. France contributes funding to 30 studies, bringing the combined total from these three countries to over 61%. Additionally, 15 studies are financed exclusively by West African project funding, categorized as "self-referential", e.g., Nigeria is the source of funding for a study in Nigeria [76,77]. Fourteen studies were funded by China, while the European Union has directly supported nine publications. Summing all country distributions together reveals that Europe accounts for 54% of the funding for the reviewed articles.

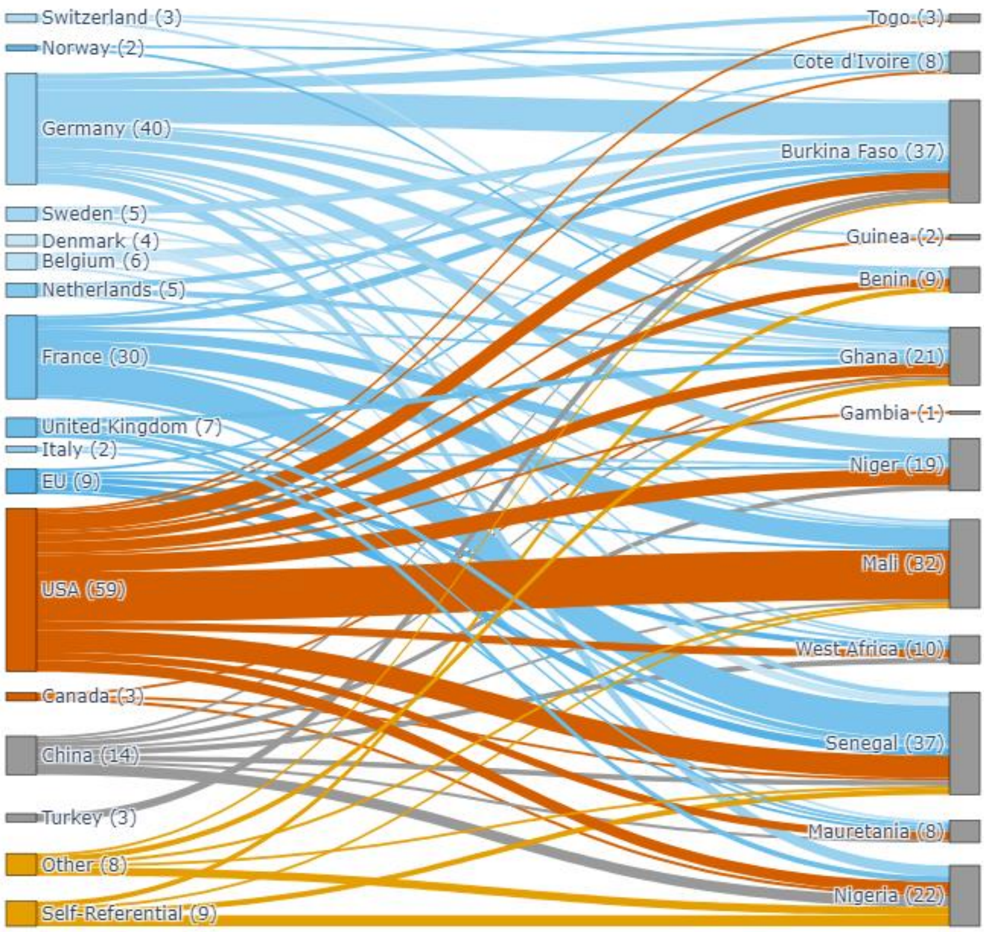

Figure 6. Sankey diagram showing the connections between funding countries (left nodes) and study areas (right nodes) of the reviewed publications. Self-referential connections indicate studies funded by sources within the studied country. The categorization represents the country of origin, without differentiating between types of funding source, such as governmental programs, non-governmental organizations (NGOs), or private investments. If no specific funding source was listed, the first authors primary affiliation was used as the funding organization. The category "Other" includes all countries with only one study's funding source. The color scheme categorizes funding sources by continent: blue for Europe, orange North America, grey for Asia, and yellow for Africa. The numbers represent the study counts.

3.3. Sensors and Sensor Types

The choice of sensor is mainly determined by the study's focus and specific objectives. Different sensor technologies exhibit varying degrees of suitability for mapping small-scale agriculture and cropping systems. Furthermore, the characteristics of the study area are influenced by the sensor selection. There are several types available, each suited to distinct applications. For measurements in visible and infrared wavelengths, active sensors such as Light Detection and Ranging (LiDAR) are employed, while passive sensors rely on the electromagnetic energy from the sun which is reflected by the earth and subsequently received and measured. Passive sensors operating across the visible to infrared spectrum are broadly classified as optical sensors, with further differentiation based on their radiometric resolution, including multispectral, hyperspectral, and thermal sensors [27,68,70]. Microwave RS can either be passive or active. Passive microwave sensors, such as radiometers can measure the emitted microwave wavelengths, but their intensity is relatively low. Active microwave sensing, achieved through Radio Detection And Ranging (RADAR) enables the assessment of measuring terrain properties, canopy structural properties, moisture status, or flooding [29,71,72].

RS is a vital tool for EO, offering timely, repetitive, and cost-effective information on the Earth's surface. It allows for data collection without direct physical contact, and advances in RS technology have led to numerous techniques for capturing data across the electromagnetic spectrum [27,68,70]. The utilized sensors, sensor types, and platforms are shown in Figure 7, respectively. It is important to note that all sensors utilized in each study are enumerated; consequently, multiple entries per study may be present.

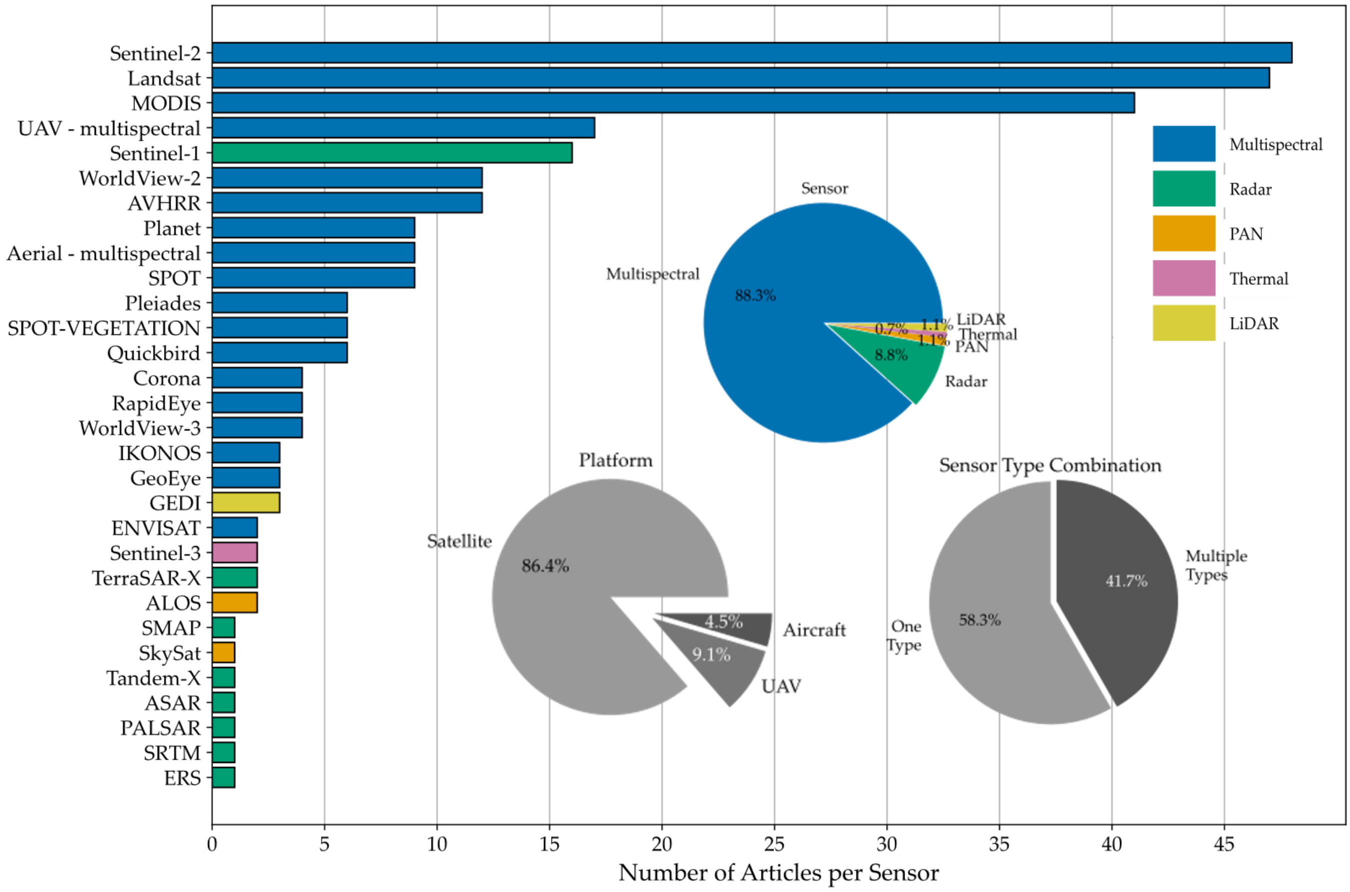

Figure 7. Overview of the different RS sensors, their platform, and the sensor type combination used in the reviewed publications. Abbreviations: MODIS, Moderate Resolution Imaging Spectrometer; UAV, Unmanned Aerial Vehicle; AVHRR, Advanced High-Resolution Radiometer; SPOT, Satellite Pour l'Observation de la Terre; GEDI, Global Ecosystem Dynamics Investigation; ENVISAT, Environmental Satellite; ALOS, Advanced Land Observing Satellite; SMAP, Soil Moisture Active Passive; ASAR, Advanced Synthetic Aperture Radar; PALSAR, Phased Array L-band Synthetic Aperture Radar; SRTM, Shuttle Radar Topography Mission; ERS, European Remote Sensing Satellite.

Multispectral sensors are predominantly used in the reviewed studies, accounting for 88.3%. The main share is allocated to Sentinel-2 (48 studies), Landsat (47), and MODIS (41), followed by multispectral UAV surveys (17). Other than these three mainly used multispectral satellite sensors, a wide range of other sensors have been used for multispectral analyses. As for RADAR analyses, the use of Sentinel-1 sensor is predominant. The only LiDAR sensor used in three publications is GEDI, a sensor mounted on the International Space Station, ISS [46,78,79]. Three studies employed PAN imaging for their analyses [22,74,75]. Two studies use thermal imaging [23,76]. There are no studies that focus on hyperspectral data. The donut chart on the left side of the figure shows that UAV missions account for 9.1% of the platforms used, while aerial is 4.5% and 86.4% is satellite borne. The UAV studies employ a variety of optical sensor systems, here classified as multispectral [77,80,81]. The aerial platform is not necessarily mounted on an airplane, e.g., Gerard et al. [82] used a balloon as a platform. There is a clear focus on the satellite-mounted sensors. The donut chart on the right shows that 41.7% of the reviewed articles employed more than one sensor as a source of data.

3.4. Temporal and Spatial Resolution

The following section analyzes the temporal and spatial resolution of RS data in the reviewed articles. Figure 8 illustrates the time periods covered by the RS data in relation to the publication dates of the studies, providing a visual comparison of data collection timelines and the timing of the study's release. Each study was classified according to the best spatial resolution of the sensors used, with the following categories: very high spatial resolution (below 10 m), high-resolution (10 to below 30 m), medium resolution (30 to below 50 m), medium–low resolution (50 to below 1000 m), and coarse resolution (above 1000 m). UAV dominate the very high-resolution category. The high-resolution category is defined by a threshold below 30 m, distinguishing between Sentinel-2 (10–20 m) and Landsat (30 m). MODIS falls within the medium-low group, while AVHRR is categorized under coarse resolution.

The temporal aspect of RS data is grouped into four categories: mono-temporal (single observation), multi-temporal (with multiple observations within one year), multi-temporal (multiple years with single observations), and time-series (with at least eleven timesteps and multiple recordings over several years).

The timeline graph shows that a large number of mono-temporal studies are categorized as high to very high-resolution, while most UAV studies are mono- or multi-temporal (intra annual). In terms of investigated time periods, 39.4% are time-series, 31.9% are multi-temporal intra-annual, 15.6% are multi-temporal inter annual studies, and 13.1% are mono-temporal studies. For example, time series studies include Maselli's work [80], which utilizes AVHRR data from 1982 to 1990 to create ten-day composite NDVI values, and Lee's 2022 [81] study, which employs a mix of MODIS and AVHRR data from 1981 to 2021. Multi-temporal (inter-annual) studies involving multiple years of single observation can be seen in Thiam's research [83], which used Landsat images from 1984, 1994, 2007, and 2017 to monitor land use and soil salinity changes in coastal landscapes of Senegal. Similarly, Traore's study [84] assessed changes in the agricultural irrigated area in Burkina Faso using Landsat images from 1987, 2000, and 2005. In contrast, multi-temporal studies (intra-annual) with multiple observations in a single year are exemplified by Forkuor's article [64], which integrates six RapidEye scenes and six TerraSAR-X images to enhance crop discrimination in the Vea watershed in the Sudanian Savanna. Lastly, mono-temporal studies focus on a single point in time, such as Roupsard's [85] UAV mission in October 2018, which evaluated the influence of individual standing trees in the Senegalese parklands on millet yields.

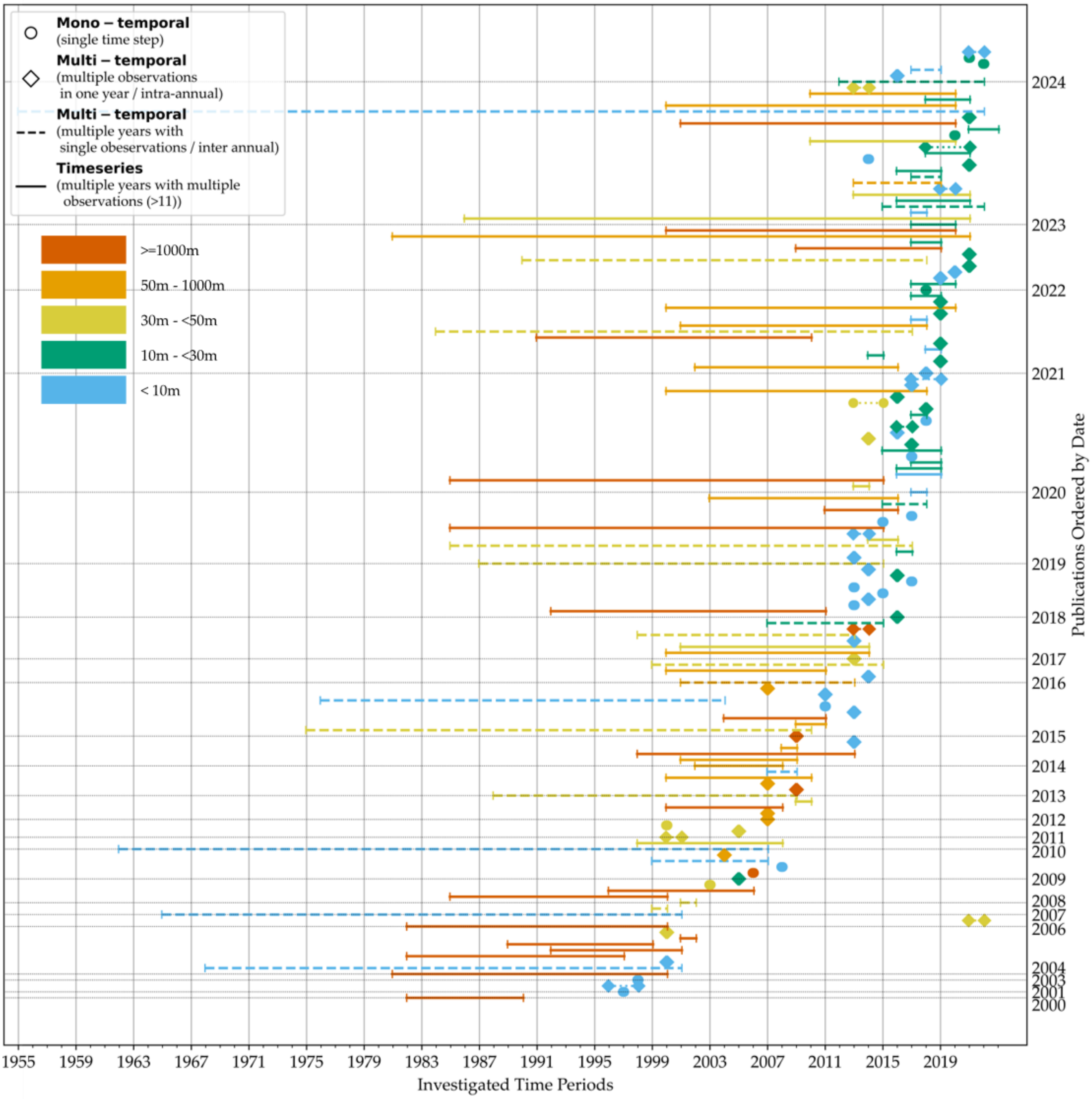

Figure 8. Overview of the time periods covered by the RS data in relation to the publication dates of the studies, providing a visual comparison of data collection timelines and the timing of the studies release.

Figure 9 shows the study area in relation to the pixel size. For studies using multiple datasets, the dataset with the highest spatial resolution has been considered in this analysis. The study area size is categorized as local (<100 km²), regional (>100 km² but smaller than district/federal level), federal/district level, national, and multinational. A total of 25.3% of the studies focus on a local-scale study area and 21% combining this local focus with a pixel size smaller than 30 m. Regional areas, defined as those greater than 100 km² but smaller than district/federal level are covered by 40.7% of the publications reviewed across all spatial resolution levels. Among these, 33.3% employ very high, high, or medium spatial resolution. As the study area size increases, the spatial resolution of the sensors used tends to increase analog. Nearly 10% (9.3%) of studies cover federal/district level, while 11.7% examine national-level areas and 13% investigate multinational area or cover whole West Africa. In terms of spatial resolution, 28.4% of studies employed very high spatial resolution data with a pixel size smaller than 10 m. Data with a spatial resolution below 30 m is used in 53.7% of the reviewed articles. Medium spatial resolution data were applied in 17.3% of the articles. In total, more than 70% of the reviewed articles used a spatial resolution lower than 50 m to assess small-scale agriculture in West Africa.

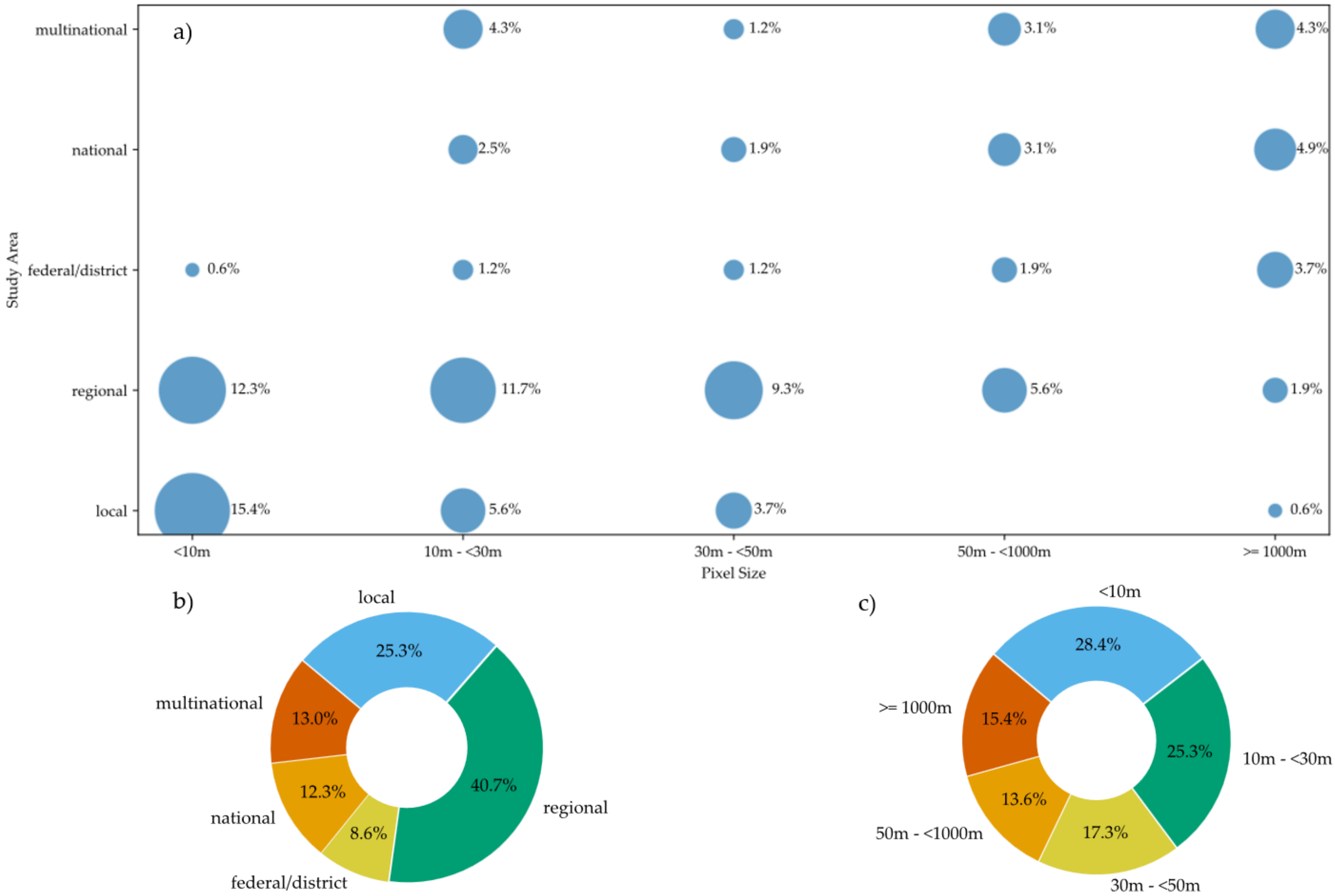

Figure 9. Overview of the study area compared to the pixel size used in the reviewed publications. (**a**) Scatterplot showing the study area compared to pixel size, with scatter size indicating the proportion of each category in the total reviewed articles. (**b**) Donut chart displaying the distribution of the study area coverage. (**c**) Donut chart showing the distribution of the spatial resolution of RS data used in the studies.

3.5. Croptype Analyses

This section provides information about the crop types investigated in the reviewed articles. Figure 10 shows a histogram displaying all the studied crops and a color-coded categorization for clarity. Notably, some studies examine multiple crops, thus multiple entries per article are possible, e.g., one study includes millet and peanut [86] or millet and sorghum [87]. Within the cereal's category, millet is the only representative, yet it is featured in 41 articles. This, in combination with the following crop types, are the four most frequently studied in the literature analyzed for this review: maize/sorghum (59 articles), trees (29 studies), and rice (25 studies). The majority of studies in the category tree are focused on cocoa [78,88] or palm oil [46,89,90]. In addition, the category "Other", investigated by 21 articles, is designed to encompass crops that do not fit into the main categories. Cassava and sugarcane are low represented in the reviewed literature. Despite there being

15 studies on cotton, it is classified as "Other" as it is a non-food crop, whereas most categories emphasize staple food crops. Peanuts, referred to as groundnuts in some literature, appear in 13 studies. This is complemented by the categories of the beans/legumes and mixed vegetables, each represented 11 times. Overall, the literature addresses the primary staple crops in West Africa as stated by the FAO in Section 2.1.

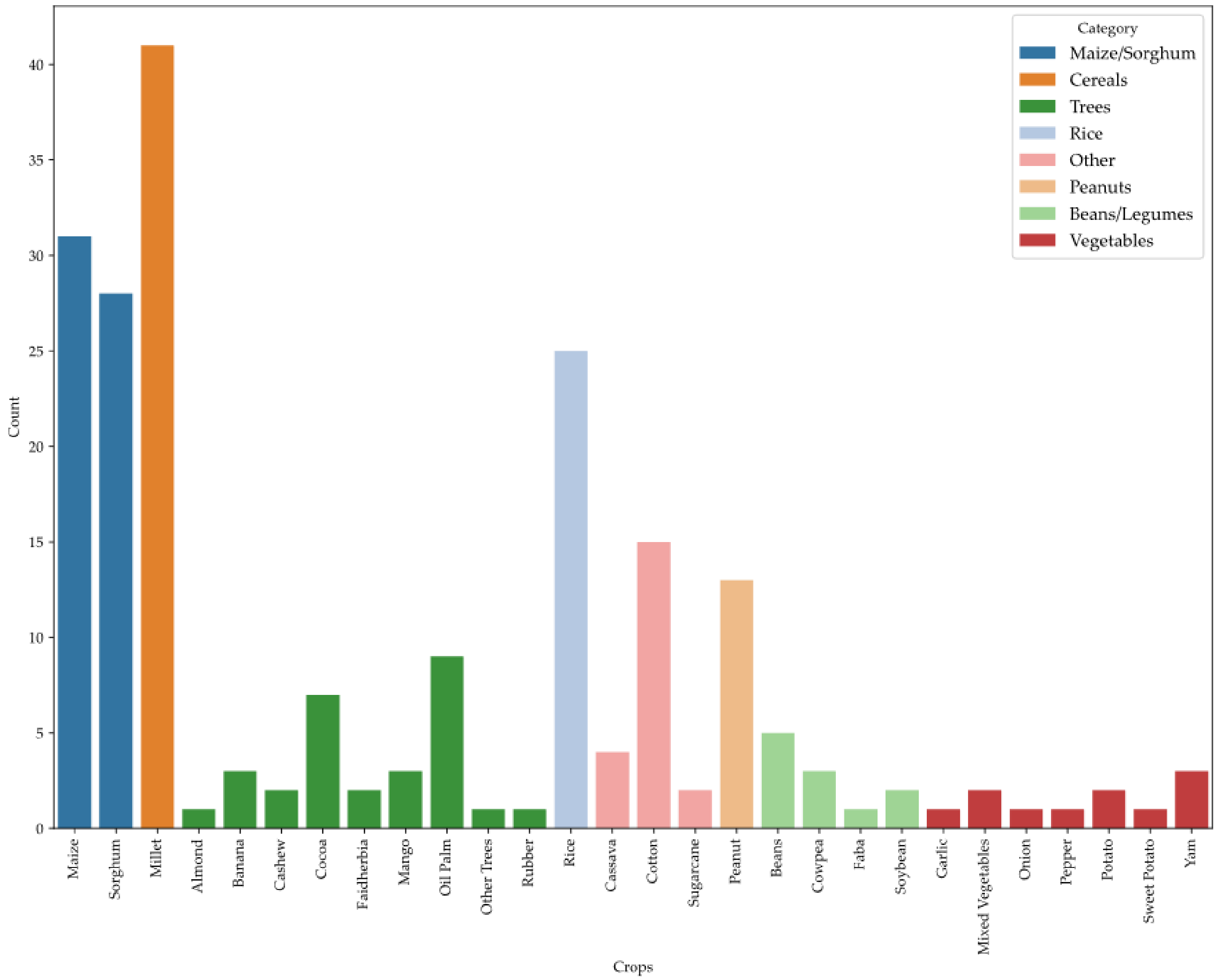

Figure 10. Histogram showing the distribution of analyzed crops by type.

Figure 11a displays a heatmap illustrating the frequency with which different crop categories have been studied across the West African countries. This provides a clear overview of the specific crop categories of interest in the reviewed articles, focusing solely on the West African countries that have been examined. The RS analyses of "Maize/Sorghum" are most prominent in Mali (21 studies) and Burkina Faso (19), followed by Senegal (9) and Nigeria (8). "Cereals" are also primarily studied in those countries and additionally in Niger. "Beans/Legumes" are predominantly studied in Burkina Faso, with fewer studies in Senegal, Nigeria, and Ghana. "Groundnut" studies are concentrated mainly on the area of Senegal and Mali, with five studies each. The category "Other" includes ten studies in Mali, with fewer in Burkina Faso (four) and Nigeria (three). In other countries fewer than three studies have been conducted in this category. Rice appears in the reviewed articles in nearly all countries, with the exception of Côte d'Ivoire and Togo. In Côte d'Ivoire, the "Trees" class dominates, accounting for almost all studies conducted in this study area (eight studies), except for one in the "Other" category. Ghana and Nigeria follow with seven studies each on “trees”, while Burkina Faso has five studies focused on that category. Vegetables have the least research interest within the framework of this review, with only three studies in each Burkina Faso, Niger, and Nigeria, and one study each in Senegal, Ghana, and Benin. The heatmap additionally indicates that all crop categories have been studied in Burkina Faso and Nigeria, followed by Ghana and Senegal missing only one category. In contrast, only two and three crop categories have been examined in Togo and Côte d’Ivoire, respectively.

This scatterplot (Figure 11b) provides a visual comparison between the importance of different crop types within a country’s agricultural sector, using two key metrics:

- Crop area proportion (blue scatters): the size and color of the blue scatters represent the proportion of agricultural land dedicated to each crop category within a country. Larger scatters indicate a higher percentage of the country’s total agricultural land is allocated to that specific crop. This metric reflects the physical footprint of crops, showing their relative importance in terms of land use.
- Economic value contribution (red scatters): the size and color of the red scatters correspond to the contribution of each crop category to the country’s overall agricultural economic value. A larger red scatter means that a particular crop plays a more important role in generating agricultural revenue. This metric highlights the financial impact of crops, regardless of their land usage, providing insides into which crops are economically more important.

The values are averages of the years 2000 to 2020 based on the FAO STAT data [57]. All data on crops provided have been incorporated and classified, but another class for animal and livestock was created and has been excluded as it is not within the scope of this review. Comparing the importance of agricultural areas to the economic value of a crop type in each country provides valuable key insights. For example, a crop may occupy a large area (large blue scatter) but contribute less to the economic value, e.g., a subsistence crop (small red scatter), suggesting low profitability or market value. Conversely, a crop with a small land footprint but a large economic impact indicates high profitability or market value.

“Beans/Legumes”, while underrepresented in the reviewed literature, hold a remarkable agricultural importance across several West African nations. In Côte d’Ivoire, Ghana, Niger, and Mauretania, more than 20% of cropland is dedicated to leguminous crops. Although their economic distribution is modest, accounting for mainly around 10% and over 20% in Côte d’Ivoire of agricultural revenue, they serve as both subsistence and cash crop. Additionally, they play a crucial role in regional food security [7].

The category “Cereals” is extensively studied, particularly in Burkina Faso, Mali, Senegal, and Niger. This research focus mirrors the economic and land use prominence of cereal cultivation in these regions. Niger, in particular, stands out with cereals occupying over 30% of its agricultural land and contributing an essential share of economic output, making them a cornerstone of the country’s agrarian economy.

In Senegal, a large agricultural area is referred to as “Groundnut basin”, which exemplifies the crop’s importance in both terms of land area and economic output. Almost 40% of the reviewed literature on groundnuts focuses on Senegal and Mali, whereas the importance of groundnuts in Mali is far less [91].

However, the category “Maize/Sorghum” accounts for the largest shares of agricultural land in most countries, with the exception of Senegal, Côte d’Ivoire, Niger, and Ghana, where it still plays a considerable role. The highest share in Mauretania is remarkable, though the country is underrepresented in the studies analyzed. As a key subsistence crop for smallholder farmers, their importance is reflected both in the reviewed literature and real-world agricultural data based on FAO [57], underscoring their central role in food production systems across the West African region.

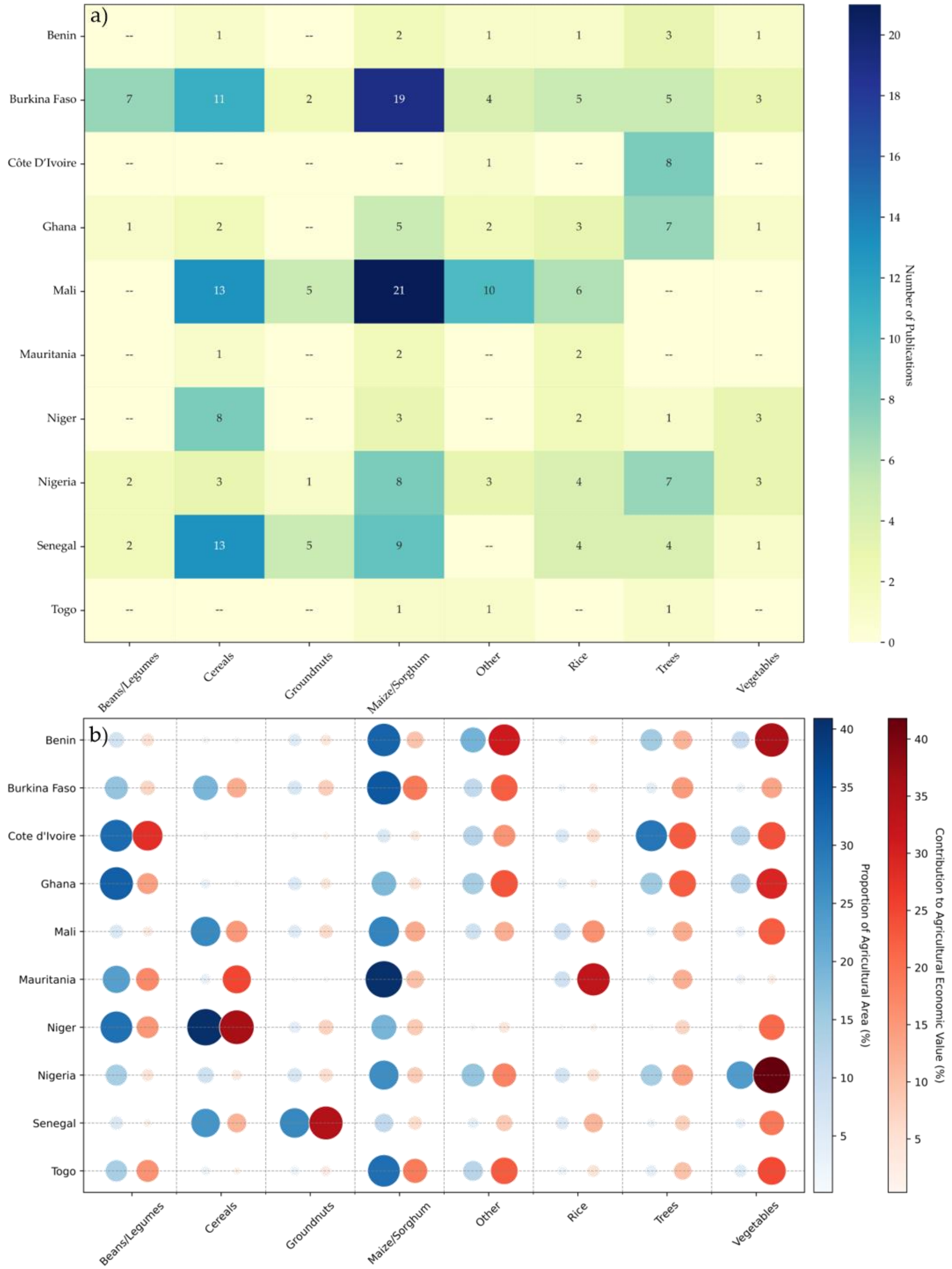

Figure 11. (**a**) Heatmap illustrating the frequency of studies on different crop categories across the West African countries, and (**b**) scatterplot comparing the importance of crop categories using crop area proportion and economic value contribution as metrics.

The crop category "Other", which includes cassava, demonstrates higher economic than spatial importance due to its status both a cash and a subsistence crop [92]. The general share of this category is nevertheless remarkably distributed across most countries, with the exception of Mauretania and Niger. In contrast, the reviewed studies focus particularly on Mali. This is due to the discrepancy between the studies in Mali focusing on cotton and sugarcane and the underrepresentation of cassava compared to the actual importance of the crop.

"Rice", while generally low in terms of cultivated area, shows its largest shares in Mali and Mauretania. In these countries, rice cultivation appeals economic attention, particularly in Mauretania, with over 30% of agricultural revenue, positioning it as a crop of considerable economic importance. Côte d'Ivoire, Nigeria, and Senegal show a certain degree of rice cultivation in terms of both proportion of area and contribution to agricultural economic value. It is notable that no studies have been conducted on rice in Côte d'Ivoire and only two in Mauretania, in contrast to five studies in Burkina Faso. The distribution of the remaining literature, as illustrated in the heatmap, reinforces the findings presented in the scatterplot.

"Tree" category crops play a minor role in most countries, except in Ghana and Côte d'Ivoire, where the cultivation of cocoa and oil palm contributes substantially to both land use and economic returns. Nigeria and Benin also have a considerable area under cultivation and economic importance. Those observations correlate closely with the regional distribution of relevant studies.

"Vegetables", despite their limited land use, consistently rank high in economic value, with Nigeria standing out for its large share of agricultural land devoted to vegetable farming. Vegetables account for over 40% of Nigeria's agricultural revenue, highlighting a contrast between vegetables economic weight, and their relatively small agricultural footprint. Notably, this prominence is less reflected in the heatmap of reviewed articles, hence the topic of the review, signaling a potential gap in these high-value crops.

3.6. Focus of the Studies

The focus of the study (Figure 12) has been split into five categories, namely the monitoring of crops, agroforestry, land use, and land use change (LULUC) analyses with specific focus on crops, climate impact, and the variables causing them and a category "Other" for the articles not classified in the abovementioned categories. Studies that analyze broad LULUC without focusing on specific crops/croplands or employ single NDVI image analyses have been excluded from this review due to their insufficient informational value. An increase in studies in "Crop Monitoring" and "Agroforestry" are the main drivers of an increased number of articles over time covering the topic of this review. "Climate Impacts", which covers drought analyses, soil moisture and evapotranspiration modeling as well as large-scale phenology of crops (greening/browning) follows.

The chosen focus is thematic, emphasizing the possibilities and limitations of RS data across various fields of application. A concise overview is provided of each study's contributions and focus. Detailed information on specific methodologies is available in the referenced original studies. It is important to note that while vegetation indices are frequently used in methodologies, this review was not specifically designed to give a comprehensive overview of VIs and their relationship to crop monitoring. Instead, the aim was to showcase the broad potential of RS applications in small-scale agriculture in West Africa. For in-depth discussions on VIs for crop monitoring and discrimination, readers may refer to specialized reviews such as those by Vidican et al. [93] or Xue and Su [94].

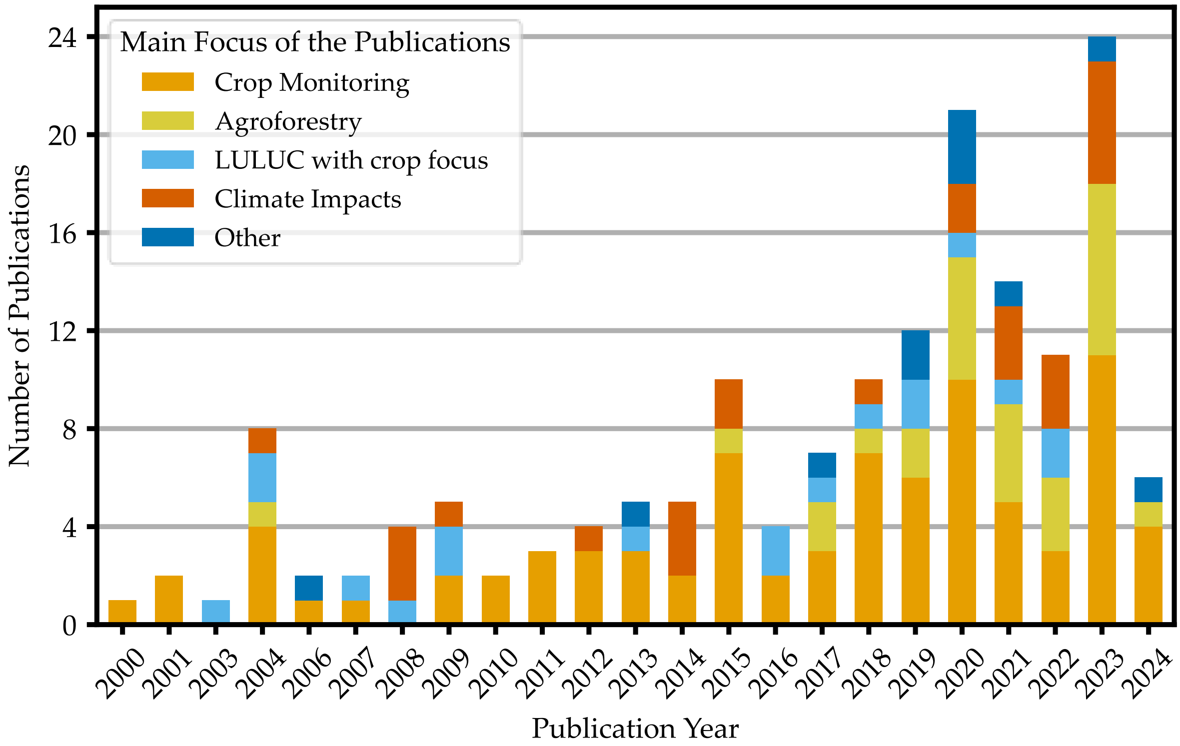

Figure 12. Histogram showing the distribution of the main thematic focuses of the reviewed publications over time.

The following categories are strict thematic divisions, as each study addresses different aspects, while exploring various possibilities of RS and facing similar challenges. This overview (Table 2) aims to provide a comprehensive summary of the RS research conducted on small-scale agriculture in West Africa:

Table 2. Overview Table summarizing the main findings, RS potential, and remaining challenges for each research focus category.

Study Focus	Category	Main Findings and Remote Sensing Potential	Challenges	Sources
Crop Monitoring	Agricultural Productivity	Estimating crop yields in a heterogenous small-scale agricultural landscape	Limited reference data for assessing accuracy of satellite-based estimates; high spatial variability	[7,33,67,80,81,95–106]
	Crop-Type Mapping	Combining optical and SAR data and a variety of methods for multi-sensor data analysis	Heterogeneity, accuracy of final products; reference data scarcity	[11,25,34,45,47,61–64,70,71,86,100,107–118]
	Plant Parameters	LAI, soil amendments, vegetation monitoring, evapotranspiration	Large within and between field variations in yield, LAI, chlorophyll, etc.	[12,82,119–128]
	Field Characteristics	Derivation of field boundaries, soil moisture and type	Small feature extraction; limitations of Proxy Use	[4,29,65,69,129–131]
	Management Detection	Water management performance; timing, impact and responses of crop management	Sustainability monitoring, reference data, data variability within fields	[1,10,37,38,77,87,132–142]
Agroforestry	Cocoa and Palm Oil	Accurate mapping of cocoa and palm oil plantation including encroached areas	Limited reference data and reference data refinement	[22,46,78,88,90,143–145]
	Fruit Trees	Fruit tree disease surveillance system	Lack of validation data	[40,146–149]
	Above Ground Biomass in Agroforestry systems	Spatially explicit AGB estimates for reporting reduction emission efforts	Site complexity, poor-quality reference data, spectral variability within the same class and mixed pixels from fragmented landscapes	[79,89,150–152]
	Semi-arid Parklands	Mapping agroforestry parklands and their influence on crop yields	Upscaling individual tree level to landscape level (diversity of tree species and mix of crop types)	[68,85,153–157]
LULUC (with crop focus)	Data Consistency	Improved accuracy (data fusion and very high-res.)	Lack of consistent LULUC maps	[30,158,159]
	Classification Accuracy	Supporting decision-making for multiple objectives	Low agreement among RS datasets	[18,32,43,66,84,160–165]
	Mapping Approaches	Diverse and new methodologies and various data integration for improved mapping of LULUC	Similar phenological signatures complicate mapping	[73,166–168]

Table 2. *Cont.*

Study Focus	Category	Main Findings and Remote Sensing Potential	Challenges	Sources
Climate Impacts	Evapotranspiration	Data fusion for daily field-scale LST and ET estimates	Lack of bias-free validation and high-resolution thermal data	[23,169,170]
	Drought and Dry Spills	Vulnerability to climate change	Limitations of RS indices	[91,171–174]
	Phenology and Greenness	Impact analysis on drivers of trends in cropland productivity, phenology and greenness	Downscaling coarse NDVI data of large area	[35,107,175–185]
Others	-- --	Flood risk management, health risks, locust habitat, fallow land assessment	Reference data scarcity, spatial resolution of RS data	[65,73,74,76,83,186–192]

Several studies (19 in this review) have explored the use of RS data for predicting crop yields and assessing agricultural productivity in West Africa. Maselli et al. (2000) [80] pioneered a cost-effective approach using AVHRR NDVI data to forecast millet and sorghum yields in Niger. Tottrup and Rasmussen [104] (2004) focused on evaluating the capacity of RS methods to assess long-term trends in crop productivity in Senegal's Groundnut Basin using similar time series data. Brown et al. (2006) [103] examined the relationship between satellite vegetation measurements and millet prices in Burkina Faso. In 2016, Leroux et al. [67] combined vegetation and thermal indices to estimate crop yields in the Sahel, while Imran et al. [102] aimed to predict sorghum yields and uncertainty across Burkina Faso's variable environmental conditions. Lambert et al. [101] addressed the challenge of assessing crop productivity in Mali's cotton belt due to spatial variability in farming practices, soil fertility and rainfall, using Sentinel-2 data and ground information to achieve 80% accuracy in crop type classification and improve yield predictions through incorporating parcel boundaries retrieved from very high-resolution imagery and leaf area index modeling. Leroux et al. (2019) [33] advanced a novel approach that integrated RS, crop modeling, and statistical methods, explaining 46% of maize yield variability two months before harvest in Burkina Faso. The Random Forest model incorporating soil moisture and canopy temperature data demonstrated the method's potential for regions with limited field data. In 2020, Karst et al. [7] utilized high-resolution Sentinel-2 data to predict household-level crop yields for various crops in Burkina Faso and assessed the suitability of different crop types using multiple linear regression. Lobell et al. [99] highlighted the variability within and between sorghum cultivars and harvest index (ratio of grain to total crop biomass), emphasizing the promise of growing high-resolution satellite data availability for monitoring plots. Sentinel-1 and 2 data were employed by Ouattara et al. [106] to map irrigated crops around Lake Bam, estimating productivity through regression analysis of fragmented small-scale farms with seasonal changes. Pignède et al. [105] explored methods for anticipating sugarcane production prior to harvest in Côte d'Ivoire using cropping practice, meteorological, and satellite data. Gbodjo et al. [97] assessed the potential of deep learning approaches with SAR and optical data compared to traditional regression methods, aiming to enhance crop yield estimation with limited reference data. In addition, yield forecasts throughout the cropping period assisted in determining how well RS-based modeling can help accelerate the collection of crop production information in the study site. Adewopo et al. [98] highlight the use of UAV-derived vegetation indices to understand yield variability at the field scale and the importance of very high-resolution imagery for rapid agronomic monitoring and robust decision support. Lee et al. (2022) [81] investigated out-of-sample forecasting skills and evaluated the benefits of enhanced temporal resolution and non-standard EO data to improve grain-yield forecasting and food security warnings across Africa. Gachoki and Muthoni (2023) focused on improving maize yield predictions under different management practices using a Random Forest model [95], while Schwarz et al. (2023) [96] aimed to develop a valid crop yield model based on a three-year in situ dataset in northwestern Burkina Faso. The aim was to reduce the need for extensive ground data collection while ensuring accurate household-level yield estimates through Sentinel-2 satellite-based crop yield models [96].

A total of 26 publications focus on the mapping of cropland areas and crop types in West Africa. In their 2011 study, Marshall et al. [112] generated unbiased estimates of crop area during Niger's principal crop-producing season in 2005, using medium-resolution satellite imagery along with high-resolution imagery. Junge et al. (2010) [25] examined historical and contemporary aerial photographs and satellite images to investigate changes in land use and cover, as well as soil degradation in Nigeria and Benin, revealing an expansion of agricultural land at the expense of forests, shrubs, fallow areas, and uncultivated land.

Ibrahim et al. (2021) [107] evaluated the accuracy of mapping maize, potato, and mixed cropping systems in Nigeria by employing the complete dataset from Sentinel-2, while also analyzing the distribution of various crop types across the study region and among different field sizes. In 2018, Soti et al. [86] developed a replicable sampling methodology using very high-resolution optical imagery to explore how landscape composition influences crop pest incidence and biological control, specifically focusing on the millet head miner. Hall et al. (2018) [110] concentrated on the delineation of maize cultivation areas within complex cropping systems in Ghana, employing UAV imagery for their analysis.

Expanding the scope, Vintrou et al. (2012) [45] and Samasse et al. (2018) [100] conducted a detailed performance assessment of various global landcover datasets, such as GLC2000, GLOBCOVER, MODIS V05, and ECOCLIMAP-II for the AMMA zone to accurately map the cultivated area in Sahelian West African countries. They employed very high-resolution imagery as reference data. Furthermore, Vintrou et al. applied various methodological approaches to map fragmented landscapes, for instance, data mining based on MODIS or utilizing coarse resolution satellite-derived metrics (spectral, textural, temporal and spatial) to assign pixels to defined crop production system in Mali [70,71]. In another study in Mali, Pitarch et al. (2015) [115] built an accurate classifier through extracted multidimensional sequential patterns with MODIS time series combined with field data. Rian et al. [118] employed MODIS data paired with 600 ground survey points to create a landcover map of Mali. They claim the ability to detect small-scale, but important, wetland features such as rice cultivation areas for regional-scale studies. Samasse et al. (2020) [47] used more than 400,000 land-cover training data points for the year 2013, paired with Landsat images to train locally optimized Random Forest models predicting the presence and absence of rainfed and irrigated agricultural fields across the non-desert area of West Africa. Irrigated areas, especially those dedicated to rice cultivation, are the subject of several publications on crop type mapping. Gumma et al. [111] mapped irrigated areas in Ghana using Landsat and MODIS, Ujoh et al. [109] identified suitable areas for rice cultivation in Nigeria, and Higginbottom et al. [114] mapped the distribution of croplands under active irrigation between 1987 and 2020 along the Senegal River based on Landsat imagery, whereas Traore et al. [116] focused on the Kou river in Burkina Faso between 1988 and 2009. In a second study, Gumma et al. [113] identified critical spatial data layers for assessing land suitability that pinpoints optimal rice cultivation areas in inland valley wetlands.

In 2020, Fiorillo et al. [108] investigated rice cultivation by combining Sentinel 1 and 2 datasets to leverage the individual advantages of each data source. Forkuor et al. [63,64] aimed to enhance the classification accuracy of multi-sensor crop mapping in West Africa by similarly combining two data sources. However, Forkuor employed optical and SAR data in a sequential masking classification to address the region's spatial heterogeneity. In a third study from 2017, Forkuor et al. [34] estimated fractional cropland cover using a subpixel approach based on MODIS and Landsat to improve the accuracy. Abubakar et al. [61] proposed a framework for integrating Sentinel-1 and 2 imagery to map maize crops, focusing on the ideal combination of Sentinel-1's dual-polarization to complement Sentinel-2 for effective agricultural applications. In a second study from 2023, Abubakar et al. [62] conducted pioneering research in Nigeria by examining the potential of the Google Earth Engine platform and machine learning techniques for mapping maize croplands in Nigeria from 2016 to 2019. For a comprehensive crop distribution map in southern Mali, in 2018, Aguilar et al. [11] evaluated a cloud-based multi-temporal ensemble classifier, integrating WorldView images and various machine learning approaches. Mohammadi et al. [117] used deep learning techniques that have recently shown promising results in crop mapping. However, the lack of labeled samples limits the classification performance. Consequently, there is a need for methods that are capable of exploiting label-rich environments to classify crops in label-scarce regions. While few-shot-learning methods have successfully adapted this issue in a computer vision for natural images, their application in crop mapping using time-series data remains largely unexplored.

Field characteristics encompass a broad range of factors, but the reviewed studies here specifically addressed parameters such as field boundaries, textural features, soil properties or the share of trees and tree species on a field.

Accurate delineation of smallholder farm boundaries is challenging due to the field's small size, irregular shapes, and mixed cropping systems. Persello et al. [4] use very high-resolution WorldView-2/3 data and a fully convolutional neural network to achieve promising results in Nigeria and Mali for detecting field boundaries. Trivedi et al. [29] emphasize the importance of satellite-derived textural features as a valuable complement to spectral and polarimetric features, finding that textural features in this study comprise half of the total significant feature analyzed. This indicates that the spatial arrangement of pixels is more important than their intensity values, as these arrangements can be described by measures of contrast, homogeneity, randomness, or variability, such as entropy or variance. The study by Sawadogo et al. [129] focused on diagnostic performance indicators such as depleted fraction, evapotranspiration, and crop water productivity to evaluate the performance of irrigated rice, aiming to identify areas with good and poor performance. The depleted fraction provides insights into water efficiency or losses from drainage or percolation. Their parameters were derived using the PySEBAL model driven by Landsat images to analyze spatiotemporal patterns. Moussa et al. [130] aimed to identify potential soil salinity areas by integrating Sentinel-2 with field measurements, employing two approaches: assessing salinity through the Salinity Index and monitoring vegetation behavior over eight growing seasons from 2016 to 2019 in the arid Niger River basin in rice fields. Forkuor et al. [65] present the results of a soil mapping approach that combined multi-temporal RapidEye, Landsat imagery, along with ASTER Global DEM terrain derivatives and soil samples to enhance the availability of spatial soil information in rural West Africa. In 2022, Leroux et al. [69] demonstrated that both tree species diversity and tree cover in semi-arid parklands are crucial for food production and enhance food security, utilizing an integrated landscape approach with current RS data and advanced data analysis methods. They advocate for land management policies that acknowledge the importance of co-benefits within the agricultural landscape diversity-food security nexus. Rilwani et al. [131] presented an approach for assessing land suitability for precision agriculture in Nigeria, combining field data on soil properties of plots with remotely sensed land use suitability.

Twelve studies addressed retrieving plant parameters. Gerard et al. (2001) [82] investigated the effects crop residues and phosphorus application have on fallow vegetation after repeated millet cultivation in the Sahel, measuring residual effects on herbaceous dry matter two years post-experiment and evaluating an RS method for herbaceous dry matter estimation. Their findings indicate that soil amendment impacts on fallow vegetation have to be considered in analyzing agro-pastoral systems. In a separate study Gerard and Buekert [126] (2001) tested non-destructive methods for spatially estimating millet growth and yield. This involved testing aerial photography, georeferenced radiometric, and chlorophyll measurements in an experiment in Niger. Sawadogo et al. (2020) [123] employed the PySEBAL model to estimate actual evapotranspiration over large areas throughout the crop growing season for water resource management. Kergoat et al. (2015) [125] used SWIR bands to detect dry season vegetation mass and cover fraction with a ground radiometer and MODIS data, which is a key parameter for forage, erosion, and fire risk assessment in semi-arid areas. Bégue et al. (2023) [122] analyzed growth vegetation anomalies produced by the crop monitors of the main early warning systems for the 2010 to 2020 period. As a comparative measure, they used NDVI-based vegetation anomaly indicators. The convergence of EO data streams, advancements in methodologies, and cloud computing infrastructure calls, according to Defourny et al. (2019) [124], for a paradigm shift in operational agricultural monitoring. They assessed whether the Sen2-Agri platform can be effectively applied to different cropping systems to provide essential agricultural information with high accuracy. Their outputs include monthly vegetation status indices, crop masks and crop type maps, with vegetation status being derived from NDVI and LAI. The LAI as a plant parameter is the subject of several studies: Fensholt et al. (2004) [121] evaluated MODIS LAI and fAPAR against in situ measurements, and Gano et al. (2021) [120] employed UAV-based vegetation indices to estimate the temporal dynamics of leaf area, shoot biomass, and plants height within a sorghum panel representative of the genetic and phenotypic diversity of African sorghum under contrasted water situations. Furthermore, Gomez et al. (2022) [147] evaluated the accuracy of the 2019 Digital Earth Africa cropland masks, developed an LAI retrieval method from Planet surface reflectance data, created a maize classification dataset for Ghana, and examined the relationship between maximum LAI and crop yield. The findings indicate that linking the yield with EO-derived metrics like maximum LAI is challenging due to significant variability in yield within individual fields. Better co-located yield and LAI measurements could improve the understanding of uncertainties in mapping canopy variables to LAI. Dembele et al. (2024) [127] calibrated and validated successfully sorghum varieties LAI values estimated from UAV at different growing seasons in Senegal and Mali. Ekwe et al. (2024) [128] assessed the LAI at the seedling stage after conducting a field experiment with rainfed groundnut based on Sentinel-2 data. In future work, they plan to include high-resolution UAV hyperspectral, RGB, and multispectral image data in the modeling process. Lastly, Diack et al. (2024) [12] addressed the limited focus on the fraction of green vegetation (FCover) due to challenges in collecting reference data. The study introduces a novel framework that effectively combines FCover data from UAVs and Sentinel-2 images to estimate FCover for millet at landscape scale in Senegal's groundnut basin.

Seventeen studies can be related to detecting agricultural management practices. Nguru et al. (2023) [132] calculated the Normalized Difference Water Index over nine years to identify flood-prone areas and assess their suitability for flood residual water cultivation based on crop reference evapotranspiration. Sawadogo et al. [133] (2020) investigated irrigation management and performance of the Kou Valley using several Landsat-derived parameters to reveal spatial differences in crop areas related to water stress, identifying low-performing water management during early and late phenological stages. Borgia et al. (2012) [136] similarly analyzed irrigation, drainage, and productivity patterns in Mauretania. Busetto et al. (2019) [1] used the PhenoRice algorithm with MODIS imagery to track rice cultivation in the Senegal River Valley, mapping variations in cultivated areas and phenological metrics. Schut et al. (2018) [134] demonstrated the use of high-resolution satellite and UAV imagery to assess yield variability and fertilizer response. Blaes et al. (2017) [10] evaluated RS's ability to detect crop status in Mali's rainfed systems, focusing on NDVI sensitivity to fertilizer treatments on cotton, millet, sorghum, maize, and peanut. Denis and Tychon (2015) [135] used RS to distinguish organic from non-organic cotton practices to aid an organic cotton certification process. Zwart and Leclert (2010) [137] presented an application based solely on high-resolution RS data to analyze strategic and diagnostic performance indicators, offering insights for improving the overall system performance. Tappan and McGahuey (2007) [138] monitored the impact of agricultural intensification, LULUC trends, and soil-water conservation practices. Soti et al. (2019) [37] measured the impact of farming practices and landscape context on the control of the millet head miner by natural enemies, hypothesizing that landscape diversity positively influences pest regulation. Fastner et al. (2023) [139] assessed the global market effects on land use sustainability and the magnitude of the regime shift from subsistence-oriented agro-pastoral ecosystems into increasingly market-oriented ones. Sidibe et al. (2021) [38] analyzed agricultural digitization in Mali, while Koglo et al. [140] (2019) monitored forest to agricultural and agroforestry transitions in Togo within the REDD+ framework. Lloyd and Dennisson (2018) [87] mapped farms that employ water harvesting or conventional agricultural techniques in Burkina Faso with Quickbird and WorldView imagery. Eniolorunda et al. (2017) [77] examined floodplain management in Nigeria emphasizing the role of extension workers to teach farmers agricultural best practice. Laris et al. (2015) [141] linked declining cotton yields in southern Mali to fertilizer misallocation, employing RS data combined with in-depth farmer interviews. Using the ALADYN model, Grinblat et al. (2015) [142] highlighted the unsustainability of traditional farming practices shown through periodic soil fertility declines to levels too low to allow for cultivation.

The "Agroforestry" category can be subdivided into four areas: (i) mapping of cocoa and oil palm; (ii) the analyses of fruit trees such as bananas, cashews, or mango; (iii) assessment of the above-ground carbon storage with focus on plantations; and (iv) mapping of semi-arid parklands with their ecological implications. Cocoa and palm oil agroforestry systems, promoted as a strategy to mitigate deforestation, require precise delineation to establish a robust monitoring system [79,90,145]. Additionally, parameter retrieval such as the age of palm oil or height of the trees is crucial for sustainability assessments, carbon mapping, yield projections, and precision agriculture [46,78,193]. However, challenges such as the lack of high-resolution imagery, mainly due to the high cloud cover of tropical regions and the quality of validation data persist [88,144]. Yin et al. utilized 2.4 m resolution Planet basemaps, 0.5 m resolution aerial imagery, two newly developed deep learning algorithms, and extensive ground truth datasets to successfully create the first national map of cashew cultivation in Benin, characterizing its expansion between 2015 and 2021 [149]. In addition, Alabi et al. [40] developed a banana disease classification system and Selvaraj et al. [147] further strengthened an approach to map bananas under mixed-complex African landscapes. Furthermore, studies by Torgbor et al. [146] and Sarron et al. [148] focused on mapping the phenology of mango trees and assessing their yield on orchard level, respectively, contributing to a comprehensive understanding of fruit tree dynamics in the region. Agroforestry systems present viable solutions for climate change due to the above-ground biomass (AGB) sustained by their tree components. Accurate, spatially explicit estimations of AGB within these systems are essential for reporting emission reduction efforts. However, several factors, such as the spatial distribution, structural diversity, composition, and their varying extents pose challenges to RS techniques. Five studies focus on assessing the RS potential of spaceborne optical, SAR, and LiDAR data for AGB estimation in agroforestry systems in West Africa [79,89,150–152]. Smallholder farming in agroforestry parklands is the predominant agricultural system in the Sudano-Sahelian zone of West Africa, serving as the subsistence base for a large proportion of the population. These parklands are agricultural landscapes defined by the coexistence of scattered trees within cultivated fields. Studies by Karlson et al., Leroux et al., and Roupsard et al. [68,85,151] examine the influence of parkland trees on crop yields at the landscape scale, considering a range of different tree cover characteristics. Other research focuses on mapping the abundance of the multi-purpose agroforest *Faidherbia albida* trees [153,155] or comparing machine learning techniques to map different tree species within the agroforestry landscapes of West Africa [156].

A total of 18 publications fall under the category "LULUC with crop specific focus", showing no clear temporal pattern or trend. However, studies in this category have to go beyond generating land use maps or tracking land use change over time. Instead, they emphasize specific crop areas or small-scale croplands, which offer more detailed insights. Land use maps are crucial tools for planning, describing the geographic distribution of land use, and supporting decision-making for multiple objectives. However, a lack of consistent and comprehensive LULUC maps for West Africa remains [158,164,194]. Schulz et al. [158] also explore the strengths and limitations of existing LULUC products and evaluate different classification approaches used. Cropland changes can serve as indicators of environmental challenges such as deforestation, desertification, land degradation, and for population growth [30]. Adhikari and De Beurs [159], for instance, compared 12 open-source RS LULUC datasets for West Africa, finding overall low agreement between them, with only 11% of the pixels matching across six datasets, further emphasizing the need for improvement in data consistency and accuracy [159]. Nabil et al. (2020) [32] aimed to identify factors causing spatial discrepancies among four RS land cover products and assess the impact of environmental factors such as elevation dispersion, field size, land cover richness, and frequency of cloud cover on these spatial differences. Results showed overall accuracies below 65% with particularly large disagreements in the Sahel zone and along the West African coast.

Duke et al. [162] developed a crop-type classification using UAV data and Sentinel-1, demonstrating a decline in model accuracy with decreasing spatial resolution. They improved results by integrating a canopy height model. Similarly, Knauer et al. [43] achieved high classification accuracy (over 90%) for Burkina Faso, where rainfed agriculture dominates, though irrigated areas and plantations have also expanded mainly due to targeted development projects. Traore et al. [84] concentrated solely on examining the land use changes in those irrigated areas in Burkina Faso. In Mali, Attia et al. [18] identified and processed the most relevant parameters to site suitability for promoting small-scale irrigation. The study presented the efficacy of the spatial modeling approach in site selection for agricultural development and smallholder livelihoods and welfare [18]. A different approach for mapping and monitoring irrigated lands was introduced by Wellens et al. [161], employing a low-cost method based on small-scale amateur aerial imaging. Their goal was to help Burkina Faso to achieve a more equitable allocation of irrigated areas, thereby alleviating water scarcity. The diversity of cropland systems across the West Africa continent are highly diverse and often adapted to very specific environmental conditions. This presents challenges, particularly as the phenological signatures of the various land use types in a region can be very similar. As a consequence, mapping croplands at a continental level requires large and up-to-date training and validating datasets. Addressing this, Sedano et al. [160] proposed a mapping approach for the agricultural systems of the Sudan-Sahelian region, designed to overcome data limitations in this area. Forkuor et al. [66] compared Landsat 8 and Sentinel-2 for assessing land use in Burkina Faso, highlighting the added value of Sentinel-2's additional red-edge bands.

Another study by Okoro et al. [168], though focused on palm oil and cropland land use change, was classified as "LULC with crop focus" instead of "Agroforestry" because the methodological approach focuses on improving LULUC maps by addressing the cloud cover issue in optical imaging based on the use of median Landsat composite images. A approach by Saarnak et al. [166] classified land use management through the use of high-resolution satellite images to detect burned areas, although distinguishing burns prior to image acquisition from neighboring areas with senescent vegetation remains challenging. Early dry season fires are often used to reduce fuel loads and maintain pastures with low impact on woody vegetation, while late dry season fires, typically accidental, cause major damage to vegetation and soil. Early rain season fires are employed in agriculture and pasture management to promote new sprouting of crops or new grass in pastures [166].

Lastly, Diuk-Wasser et al. and Dambach et al. applied their LULC mapping approach to assess malaria risk by identifying irrigated croplands, such as rice fields [73,167].

In the "Climate Impacts" category, three studies examine evapotranspiration monitoring using a range of various spatial resolutions and approaches that integrate modeling with satellite data fusion. Monitoring evapotranspiration is crucial for several reasons: (i) tracking the timing, location, and volume of water released into the atmosphere through evaporation; (ii) assessing crop performance and predicting famine by monitoring drought impacts; (iii) evaluating the irrigation system efficiency; and (iv) improving weather forecasting accuracy. Challenges include the lack of high-resolution thermal satellite data and the lack of (non-biased) validation data [23,169,170]. Five studies focused on assessing drought vulnerability in the Sahel region [91,171–174]. As the three physical types of droughts (meteorological, agricultural, and hydrological) are interconnected, a single indicator or an index quantifying an individual type of drought may proof insufficient to capture combined droughts and their related impacts. In contrast, the use of a composite drought index (CDI) provides a more comprehensive assessment by integrating different drought types [171]. The reviewed studies employ various drought indices to examine the effects of dry spells on the groundnut basin in Senegal for instance [91]. They use time-series analysis at lower spatial resolutions, as meteorological effects typically affect larger scales, deeming 1 km^2 resolution sufficient. Further reviewed studies related to climate explore vegetation health and greenness in relation to soil moisture and rainfall pattern [107,177–180]. Some research emphasizes methods to retrieve parameters like soil moisture from radar analyses [49,183]. Other studies investigated phenological parameter retrieval, such as Start of Season (SOS), Length of Season (LOS), and End of Season (EOS), and how those have evolved over time due to either climate related [180] changes or through shifts in agroecological management [182]. For instance, Mechiche-Alami and Abdi [35] state that the combined effect of recent changes in rainfall, land surface temperature and solar radiation explains approximately 40% of the variation in cropland productivity over West Africa at the 95% significance level. Other drivers are, for instance, increased inputs (irrigation and fertilizer) or land degradation [181,182,184].

The category "Other" includes studies with objectives outside the main categories. Renier et al. (2015) [195] focused on mapping vegetation senescence in arid areas using spectral indices for near-real-time monitoring, applied in Mauritania for desert locust habitat monitoring. Piou et al. (2013) [196] also employed vegetation indices to assess vegetation growth post-rainfall to map locust habitats. Alvarado et al. (2023) [188] used Sentinel-2 data for mapping non-active agricultural land in Burkina Faso, employing machine learning for high-resolution fallow land detection. Barteit et al. (2023) [187] developed and implemented the Change and Health Evaluation and Response System (CHEERS) as a methodological framework for better adaptation policies in low-income regions. Thiam et al. (2021) [83] investigated land use changes in Senegal's Djilor district to improve land management practices. They evaluated soil salinity as a key indicator for identifying practices that mitigate the adverse effects of increasing soil salinity. Sall et al. (2020) [189] analyzed hydraulic data and satellite imagery to understand water constraints and flood-recession agriculture in the Senegal River Valley. Thomas et al. (2020) [190] developed an open-source, scalable method for fusion of very high-resolution imagery with multispectral SAR and thermal data, enabling detailed mapping across large areas and multi-year analysis for small-scale agriculture mapping. Mueller et al. (2023) [192] demonstrated the impact of climate change-induced flooding on crop failures in Burkina Faso. Tong et al. (2017) [186] linked NDVI trends to changes in cultivated areas in the Sahel, specifically focusing on fallow fields. Kpienbaareh and Luginaah (2019) [191] explored the relationship between wildfires and food security in Ghana. Diuk-Wasser et al. (2004, 2006) [73,74] used RS data in two studies to identify malaria vector habitats in Mali's rice fields. Odiji et al. (2024) [76] mapped flood impacts, such as inundation extent and frequency, employing Landsat, Sentinel-1 SAR, and Sentinel-2 in the confluence region of rivers Niger and Benue to inform flood risk management.

4. Discussion

4.1. Comparative Analysis of Crop Importance in West African Agriculture: Limitations and Key Findings

Section 3.6 compares the importance of different crop categories within a country's agricultural sector, using two key metrics: crop area proportion and economic value contribution. However, these categorizations introduce some limitations. The data reflects average values from 2000 to 2020, so they represent relative shares rather than absolute values. Additionally, crop categories aligned with the FAO STAT database [57] may include crops not specifically represented in the reviewed literature. The shares do not necessarily sum to 100% because livestock and fallow land are not accounted for.

Remarkably, despite limited representation in the reviewed literature, vegetables play a substantial economic role. This discrepancy could be due to the relatively small plots occupied by cash crops like vegetables, which makes them challenging to analyze using RS techniques. Also, the review's focus on RS implies that non-RS studies on vegetables are not taken into account, as RS typically favors larger spatial analysis [106,137,161]. Only in recent years has very high-resolution RS has been widely used to analyze smaller plots, such as those for vegetable cultivation. One of the few studies addressing vegetables, specifically tomatoes, is Ouattara et al. [106].

In contrast, crops such as maize and sorghum are well represented in the reviewed literature and occupy a large share of the agricultural landscape in West Africa [47,61,62,107]. Similarly, cocoa und oil palm are extensively studied and economically important in countries like Ghana and Côte d'Ivoire, aligning with the real-world context described by Abu et al. [145] and Tamga et al. [79]. Beans, on the other hand, are covered by only a few studies, primarily focused on Burkina Faso. However, beans are also important in other countries, such as Côte d'Ivoire and Ghana, where the cloud cover poses challenges for RS analyses. In these regions, tree crops can be monitored with Sentinel-1 or other radar instruments that operate effectively despite cloudiness [46,79].

4.2. The Need for Integration of New and High-Resolution RS Datasets and High Quality Reference Data

As the analysis in Table 2 of possibilities and remaining challenges of RS on small-scale agricultural and cropping systems in West Africa shows, there is a clear need for (i) integrating various sensor data and existing data sources, (ii) employing very high-resolution data, (iii) discovering new data sources, and (iv) basing the methods on high-quality reference data [29].

i. Many studies have already employed multiple sensors in their analyses to address issues such as sparse data coverage, cloud cover, or the need to combine UAV data with satellite imagery [134]. This highlights the importance of integrating various sensors and satellite data to overcome some of the limitations related to the spatial-temporal-radiometric resolution restrictions. The topic of data fusion is extensively discussed in the recent literature [23,190,197]. Data fusion in RS offers substantial advantages by combining datasets of different modalities and resolutions to maximize their utility. For example, very high-resolution imagery can be fused with lower-resolution but more temporally frequent data, enabling precise field mapping while capturing dynamic processes such as crop growth. Advanced methods, such as deep learning, further enhance these applications, making data fusion a powerful tool for agricultural monitoring. However, challenges such as scalability for regional studies, high computational demands, and data compatibility issues limit its broader adoption, especially in resource-constrained regions. Despite these challenges, data fusion remains essential for addressing the complex needs of small-scale agriculture in West Africa [23,190,197]. In addition, several studies [67,99,106] point out that radar data are underutilized, a finding supported by the analysis of this review, which shows that only 8.8% of the reviewed articles employed radar data. Moreover, incorporating textural feature data or canopy height information retrieved from RS data have shown to enhance the results [29,78,98,193].

ii. More than 70% of the studies use spatial resolutions higher than 50 m, with over 50% using resolutions higher than 30 m. This clearly illustrates the importance of the spatial resolution in addressing the variety, heterogeneity, small and irregularly shaped fields, and varied crop calendars of small-holder farming systems. The wide range of farming practices and resource availability (e.g., fertilizer, irrigation) emphasize the need for high temporal resolution in satellite data collection [7,110]. This is further supported by the prevalence of time-series analyses and studies with multiple observations in a single year, showing the importance of time resolution for retrieving information through RS data. To effectively link household food security to satellite data, high resolution in both time and space is crucial [7,47]. The rapid advancement of methods, especially in artificial intelligence, combined with the increasing availability of high-resolution spaceborne data are expected to noticeably influence the trends of future satellite-based research. These innovations enable the extraction of more nuanced and accurate insights from vast datasets, improving applications like crop monitoring, land use classification, and yield prediction. As big data analyses continue to evolve, challenges such as processing efficiency, model scalability, and the integration of multi-model datasets may be mitigated, paving the way for more robust, scalable, and actionable insights in satellite-based research [198]. To overcome the limitations, future research could require smaller and more cost-effective platforms, such as CubeSats, which function as a unified system or constellation. They provide higher spatial resolution well below 10 m, daily revisit times, and present substantial opportunities when paired with data fusion to assess remaining challenges [199].

iii. Forkuor et al. (2015) [64] found that overlapping crop calendars can result in similarities in the spectral profiles of different crops. This can be attributed to similarities in their growth stages and cropping schedules. Moreover, high spectral variability and within-field heterogeneity, which may be influenced by factors such as soil fertility, soil moisture conditions and pests or diseases, further complicate crop differentiation. Cropland systems across West Africa are highly diverse and often adapted to very specific environmental conditions, making it challenging to distinguish different land use types based on their spectral phenological signatures alone. To address these challenges, one potential solution is the use of higher radiometric resolution, as offered by hyperspectral missions like EnMAP [128,200]. Integrating such data could, for instance, enhance the effectiveness of approaches aimed at distinguishing similar crops and land use types. Similarly, Gano et al. [120] (2021) suggest using data from other modalities like thermal or LiDAR to improve the models in the future.

Hyperspectral, thermal, and LiDAR missions offer transformative potential for improving the monitoring and management of small-scale agriculture in complex and diverse regions such as West Africa. Hyperspectral missions excel in capturing fine spectral details across a broad range of wavelengths, allowing for precise differentiation of crop health, soil properties, and environmental variables. This capability supports more accurate yield forecasts, soil assessments, and early detection of crop stress and disease, allowing for timely interventions and optimized resource use However, their application is hindered by the computational intensity of data processing, limited spatial resolution for small-scale contexts, and relatively high cost and restricted availability of hyperspectral sensors compared to multispectral systems [200]. Thermal RS complements hyperspectral data by providing critical insights into crop and soil thermal properties, directly linked to water stress, irrigation needs, and soil moisture content. In West Africa, where agriculture is highly dependent on seasonal rainfall and vulnerable to drought, thermal data becomes invaluable for identifying water-deficient zones and improving irrigation practices. When integrated with hyperspectral and multispectral data, thermal sensing enhances the depth and reliability of agricultural assessments. Nevertheless, its lower spatial resolution and susceptibility to atmospheric conditions, such as cloud cover, can limit its precision and effectiveness [201]. LiDAR further enriches the potential of remote sensing by offering three-dimensional structural information about crop canopies and terrain. These data can improve biomass estimation and land use mapping, critical for understanding the dynamics of small-scale agricultural systems. As these technologies evolve, integrating hyperspectral, thermal, and LiDAR data, alongside advancements in computing capacity, holds promise for overcoming current limitations and unlocking new applications tailored to the challenges of small-scale farming in West Africa [46,202].

iv. As indicated in Table 2, several studies criticize the lack and quality of reference data for small-holder farms in West Africa. High quality and abundant unbiased reference data are crucial to improve and validate the accuracy of RS methodologies, particularly in heterogenous landscapes [117,119,203]. Such data, used for training and validation, are critical for enhancing results. Inadequate or insufficient data can lead to overfitting and pose challenges in maintaining the performance of deep learning methods [50]. Several articles noted the scarcity of validation and trainings data [29,33,36,50,144,160], underscoring the need for reliable reference datasets. Zhang et al. 2018 [36] employed a phenology-based classification method as it has shown advantages when reference data, here field survey data, is too scarce. While sampling plays a key role in mapping agricultural systems, obtaining reliable data, for instance from remote areas, can be difficult [144]. Addressing these gaps could involve sharing databases or using very high-resolution satellite imagery as validation. Mapping croplands requires extensive and up-to-date training and validation datasets, which is why Sedano et al. [160] for instance, proposed a mapping approach tailored to overcome the limitations of the agricultural systems of the Sudan-Sahel region.

4.3. Socio-Economic Barriers to Remote Sensing Adoption in West Africa

The adoption of RS technologies in West Africa faces substantial socio-economic barriers, including high costs of advanced RS technology, limited technical expertise, and low educational levels, which hinder widespread implementation. Regional research institutions are further constrained by high publication fees, inadequate funding opportunities, and limited institutional capacity to support RS-based initiatives. Restricted access to digital datasets, inadequate or lack of capacity-building programs, and a general lack of RS awareness among stakeholders exacerbate these challenges [13,20,204,205]. To overcome these barriers and ensure the sustainability of measures the following elements revolve: (a) design and adaptation, (b) user and policy orientation, (c) education and training, (d) outreach and communication, (e) monitoring and evaluation, and (f) funding [206]. More specifically, this involves deploying low-cost sensors, promoting open datasets, and leveraging open-source software supported by cloud computing to lower financial entry barriers and enhance accessibility [204,205]. Strengthening technical, financial, and management skills through capacity-building programs is critical for empowering rural populations and fostering expertise. Partnerships, cooperative research projects, and mutual funding opportunities can facilitate knowledge sharing and resource pooling across institutions [21,205,206]. Connecting RS applications to climate change mitigation funds and embedding them into frameworks such as ISFM or System of Rice Intensification (SRI) can enhance their financial viability and effectiveness. Integrating these efforts into a holistic strategy will improve agricultural resilience, enable access to crucial funds, and ensure sustainable development in West Africa [20,21].

4.4. Limitations of This Review

This review centers on the three topics "Remote Sensing", "West Africa", and "Small-Scale Agriculture and Cropping Systems". A total of 163 selected articles were analyzed. The preselection of those articles was limited by constraints in the search string and in the Web of Science database, which is widely recognized for providing reproducible and transparent search results. However, using a different search system may result in slightly varying number of articles. As databases and search functionalities are regularly updated, the performance results in this study may change over time [207]. The use of Boolean expressions like "AND" make the searches highly sensitive, necessitating precise keyword formulations by the authors. For instance, the keyword "field*" retrieved numerous for this review irrelevant articles, while the relevant ones were included by adjusting other keywords in the search string. Combining the three topics with Boolean "AND" helped to clearly define the scope of this review.

Another limitation lies in the potential bias, as the second filter and all classifications were performed manually, introducing some subjectivity. The boundaries between certain categories were challenging to establish, leading to a degree of uncertainty. However, we have defined these categories based on our best knowledge and judgment, consistently aiming to base the processes on well-established and pre-defined criteria. Table S1 is important for providing a comprehensive overview and for ensuring transparency.

For instance, the first author affiliation is considered, and although some studies are authored or co-authored by (West) African researchers, they may be linked to non-African countries or funded projects through collaboration. A specific first author example is Gerald Forkuor, who has two publications from 2014 and 2015 affiliated with Germany [63,64] followed by three publications affiliated with WASCAL in Burkina Faso [34,65,66]. Studies with affiliations from West Africa account for less than 21%, a relatively low percentage. Additional factors contributing to this underrepresentation could include high publication fees and limited access to research funding in West Africa.

A debatable aspect of this review is the inclusion of low-resolution RS studies, such as those utilizing MODIS or AVHRR data. While these studies are limited in their ability to directly analyze small-scale agriculture, their inclusion was justified as they serve as an additional data source in RS-data-scarce regions. Despite their low spatial resolution, their high temporal resolution is particularly valuable in seasonally cloud-prone areas. This approach aims to provide a comprehensive overview of the potential and progression of Earth Observation in predominantly small-scale agricultural regions.

Additionally, some relevant publications may not have been included in the search results, despite efforts to minimize this risk. While limitations in this review exist, it still provides a thorough overview of RS on small-scale agriculture and cropping systems in West Africa.

4.5. Future Research Directions

Smallholders require options that offer relatively low risk while still providing short term returns on investment. Consequently, building resilient systems is essential for both risk management and long-term sustainability. Achieving this requires investments that go beyond plot-level technologies, extending to policies and institutional measures that facilitate adoption and help reduce risks for small-scale agriculture and farming systems in all means [7,13,208]. In this context, RS can play a vital role by providing the data and insights needed to make informed decisions at various levels, from field management to policy-making. The reviewed literature, as displayed in Table 2, already highlights the considerable potential of RS while also acknowledging its current limitations. As the field continues to evolve, advancements in RS data quality, the availability of high-quality reference datasets, and methodological approaches are anticipated. Building on those findings, several research gaps, and opportunities for future development should be emphasized. These areas represent important directions for advancing the field and addressing existing limitations:

- Integrating multiple data sources from RS and non-RS origins, such as field measurements and socio-economic datasets, will help to overcome the spatial, temporal, and radiometric constraints. This integration enhances crop monitoring, yield predictions, and contextual understanding, enabling more accurate and targeted solutions for small-scale agriculture.
- Future research should focus on leveraging advancements in artificial intelligence and data fusion to revolutionize satellite-based applications. By integrating diverse datasets, including high-resolution and multi-sensor data, these methods could enable breakthroughs in precision crop monitoring, yield prediction, and land use analysis. Addressing challenges such as processing efficiency, model scalability, and effective multi-source data fusion will be key to unlocking the full potential of these technologies for more robust and actionable insights [198].
- Advancing crop monitoring and management practices through the development of new methods for the detection of phenology and agricultural interventions, including irrigation plans, number of cropping seasons, and plant residue management. This progress will help optimize resource use and inform targeted interventions [62,100,107,108].
- An increased prominence of radar data, in particular SAR will play a crucial role in overcoming challenges posed by cloud cover in West Africa. The anticipated launch of Sentinel-1C in late 2024 is expected to further expand capabilities for all-weather monitoring of agricultural areas [209].
- Advances in daily high-resolution imagery will support near real-time crop monitoring, enabling timely decision-making for farmers and stakeholders to improve productivity and respond effectively to environmental challenges.
- Enhanced retrieval of plant parameters, such as LAI and chlorophyll content, will provide more detailed and frequent information on crop health, growth, and conditions, improving precision agriculture practices.
- The evolution of methods to derive field plot properties, such as soil characteristics, landscape organization [71], and field boundaries, will provide critical data to support smallholder farmers. This includes facilitating access to financing and insurance for smallholder cropping systems by offering accurate and actionable insights [203,210].
- The continued refinement of hyperspectral data will enhance the detection of non-photosynthetic vegetation (NPV), leading to better quantification f crop residues and biochemical traits. This will contribute to a deeper understanding of soil health and sustainable farming practices [211].

- The development of monitoring systems for sustainable intensification practices is set to enhance resource use efficiency, encompassing water, energy, fertilizers, and soil. By transforming farm management into an information- and knowledge-driven business, these systems aim to optimize agricultural productivity while minimizing environmental impacts. "Smart Farming" leverages crop-growth models and remote sensing data to make precise decisions on crop selection, sowing schedules, fertilizer and pesticide applications, and harvesting times. This approach enables efficient, location-specific management of fields, contributing to both sustainable agriculture and food security [200].
- Embedding climate adaption considerations into the design and interpretation of RS datasets will enhance their relevance for addressing climate resilience challenges.
- Establishing new publicly accessible reference databases, such as the World Cereal database provided by ESA, will facilitate broader sharing of high-quality reference data for future research and applications [212].

5. Conclusions

This review offers an analysis of the potential of RS for mapping small-scale agricultural and cropping systems in West Africa. A search string comprising relevant terms was developed through both automated and manual filtering techniques, resulting in the identification of 163 relevant studies published between 1 January 2000, and 31 April 2024. Data were gathered from these studies on several aspects: study locations, author and funding origins, the sensors utilized, as well as their spatial and temporal resolution, and the time periods examined. Furthermore, the review explored the crop types studied, comparing their representation in the research literature to their actual importance in terms of area coverage and economic contribution. Lastly, we examined the research objectives, the potential of RS, and its associated challenges. Key findings are summarized as follows:

- We identified an overall increase in research activity over time on mapping small-scale agricultural and cropping systems in West Africa, with over 53% of the reviewed publications since 2019.
- Europe dominates both the number of first author affiliations (49.7%) and the origin of funding (54%). The second-highest percentage of first author affiliations are from Africa (20.9%). Additionally, the United States shows a great research interest with 25 first author affiliations and 59 studies funded. The research hotspots in West Africa are identified as Senegal, Burkina Faso und Mali, together accounting for over 50% of the reviewed articles.
- Multispectral optical data are employed in 88.3% of all studies. About 86.4% use satellite data as a carrier system and over 58% of studies utilize more than one sensor in their analyses.
- Time-series is the predominant temporal resolution (39.4% of studies), followed by multi-temporal (multiple observations in a single year) with 31.9%, multitemporal (single observations in multiple years) 15.6% and mono-temporal with 13.1%.
- Sensors with a spatial resolution of below 30 m dominate, making up 53.7% of all studies. In addition, 66% of the reviewed articles focus on a study area at regional or local scales.
- The analysis of crop categories analyzed in the reviewed studies revealed:
    - Cereals, particularly millet, maize, and sorghum dominate the literature, with high research attention in countries like Mali, Burkina Faso, Senegal, and Niger, reflecting their land use and economic importance of those crops in these regions

- ◦ Groundnuts are a major focus in Senegal's "Groundnut basin", highlighting their dual role in land area and economic output, while crops like "Beans/Legumes", though underrepresented in the literature, contribute largely to food security and account for a large share of agricultural area in countries such as Côte d'Ivoire, Ghana, Niger, and Mauretania
  - ◦ The category "Tree", notably cocoa and oil palm, are economically prominent in Ghana and Côte d'Ivoire and is well-represented in the reviewed literature
  - ◦ There is a potential research gap of RS on high economic important vegetables in West Africa
- The analysis of possibilities and remaining challenges of RS on small-scale agricultural and cropping systems in West Africa reveals two major findings:
  - ◦ Major advancements in agricultural monitoring and LULUC mapping have occurred. Key findings include enhanced crop yield estimation in heterogeneous landscapes, accurate agroforestry system mapping, refined assessments of plant and field characteristics and crop management responses. Additionally, the integration of various data sources supports decision-making on various levels for climate change adaptation, flood risk management, and public health.
  - ◦ Clear needs include (i) integrating various sensor data and existing data sources, (ii) employing very high-resolution data, (iii) discovering new data sources, and (iv) basing the methods on high-quality reference data

Therefore, RS can largely contribute to more sustainable small-holder agriculture in West Africa by supporting practices such as sustainable intensification and integrated soil fertility management. However, its role is embedded in an ever-changing landscape of evolving socio-economic and climate conditions and variability in farming systems and information asymmetries. This poses challenges and risks requiring RS as a critical component to be used alongside other strategies for effective agricultural development [10,12,16].

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/land14010171/s1, Table S1: Overview of the 163 reviewed publications, including authors, title, sensor names, spatial resolution in meters, study country and crop of interest.

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