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Review

Monitoring Agricultural Land Use Intensity with Remote Sensing and Traits

Angela Lausch [1,2,3,*], Jan Bumberger [4,5,6], András Jung [7], Marion Pause [3], Peter Selsam [5], Tao Zhou [8,2] and Felix Herzog [9]

[1] Department of Computational Landscape Ecology, Helmholtz Centre for Environmental Research–UFZ, Permoserstr. 15, D-04318 Leipzig, Germany
[2] Landscape Ecology Lab, Geography Department, Humboldt-Universität zu Berlin, Unter den Linden 6, D-10099 Berlin, Germany
[3] Department of Architecture, Facility Management and Geoinformation, Institute for Geo-information and Land Surveying, Anhalt University of Applied Sciences; Seminarplatz 2a, D-06846 Dessau, Germany
[4] Department of Monitoring and Exploration Technologies, Helmholtz Centre for Environmental Research-UFZ, Permoserstr. 15, D-04318 Leipzig, Germany
[5] Research Data Management—RDM, Helmholtz Centre for Environmental Research-UFZ, Permoserstraße 15, D-04318 Leipzig, Germany
[6] German Centre for Integrative Biodiversity Research (iDiv) Halle-Jena-Leipzig, Puschstraße 4, D-04103 Leipzig, Germany
[7] Faculty of Informatics, Institute of Cartography and Geoinformatics, Eötvös Loránd University, Pázmány Péter sétány 1/A, H-1117 Budapest, Hungary
[8] Ludong University, School of Resources and Environmental Engineering, Middle Hongqi Road 186, 264025 Yantai, China
[9] Agroecology and Environment, Agroscope, Zürich, Switzerland
* Correspondence: angela.lausch@ufz.de; Tel.: +49-341-235-1961; Fax: +49-341-235-1939

Abstract

The intensification of agricultural land use (A-LUI) has significant environmental and economic impacts worldwide, including soil degradation, water quality problems, loss of biodiversity and increased greenhouse gas emissions. Monitoring agricultural land use intensity is a major challenge due to the complexity of the underlying processes and the spatio-temporal variability. This review summarises and compares definitions and standards of A-LUI at national and international levels (FAO, OECD, World Bank, EUROSTAT). It also discusses both in-situ methods, which provide high local accuracy, and remote sensing (RS) approaches for deriving A-LUI indicators, which allow for area-wide, temporally dense and standardised coverage. The use of RS offers significant advantages for large-scale and continuous assessment of A-LUI, while specific challenges remain, such as the assessment of small-scale structures, seasonal dynamics and management practices. The paper proposes a novel definition and structuring of RS-based LUI indicators, which includes five main features: Trait LUI indicators, Genesis LUI indicators, Structure LUI indicators, Taxonomic LUI indicators and Functional LUI indicators. These characteristics allow better access to and understanding of agricultural indicators derived from RS data. Examples of indicators for these five main characteristics are discussed. Finally, innovative technologies and approaches, including hyperspectral RS, artificial intelligence and semantic data integration, are highlighted that may be instrumental in improving the monitoring, derivation and assessment of A-LUI in the future. Finally, a comprehensive compilation of A-LUI indicators that can be derived from RS data is provided. In order to successfully establish biodiversity credits in the future, a standardised and globally comparable assessment of A-LUI using efficient indicators is required. These financial instruments could make sustainable agriculture economically attractive and thus contribute significantly to the protection and restoration of biodiversity.

Keywords: land-use intensity; agricultural land-use intensity; agricultural intensification; remote sensing; earth observation; traits; in-situ; monitoring

1. Introduction

Agricultural intensification represents a major economic development in recent decades on a global scale. However, this phenomenon is concomitant with significant environmental and economic changes, disruptions and challenges. Agricultural intensification, otherwise termed land use intensity (LUI), is defined here as the augmentation in production output per unit of land through the increased management intensity (utilisation of high yielding crops and livestock, inputs such as fertilisers, pesticides, drainage or irrigation, mechanization) and/or the adaptation of landscape structure (increased field size through e.g. land consolidation, removal of structural elements) [1]. While increasing LUI has facilitated the procurement of sustenance for an expanding global population, it goes along with substantial ecological concerns, including soil degradation, alterations in water quality and resources, biodiversity loss, augmented greenhouse gas emissions,, in addition to health hazards. For instance, the ongoing utilisation of synthetic fertilisers has resulted in soil acidification, thereby impacting the availability of nutrients to plants and the health of soil microbiota [2]. Furthermore, the excess application of fertilizers can lead to significant nitrogen leaching and run-off of phosphorus, impacting water resources and soil fertility [3].

The utilisation of heavy agricultural machinery leads to soil compaction, resulting in a reduction in both water and air permeability. This, in turn, has the potential to precipitate the occurrence of erosion and desertification over time [4]. The intensive use of water resources, which accounts for approximately 70% of total water consumption in agriculture worldwide [5], increases pressure on surface and groundwater, especially in regions where water is scarce. The quality of water is diminished by the mobilisation of salts due to low water tables and the introduction of fertilisers and pesticides into the underlying aquifers, which can threaten drinking water supplies [6,7]. Another pertinent issue is the escalating eutrophication of water bodies due to excessive nutrient inputs, which culminates in oxygen depletion and the demise of aquatic organisms [8]. Land use intensification exerts a profound influence on biodiversity [9–12]. The phenomenon of biodiversity loss [13] and the alteration of networks between biodiversity, ecosystem functions and services [14] are also impacted by land use intensification. The establishment of monocultures has resulted in the displacement of species-rich ecosystems, which in turn has been shown to lead to a decline in biodiversity, genetic impoverishment and reduced resilience. Furthermore, the process of intensification has been shown to result in a multi-trophic homogenisation of grassland communities [15]. These developments have consequences for the resilience of ecosystems, resulting in the loss of essential ecosystem services such as pollination, pest control and soil formation [16–18]. The expansion of agricultural land, frequently at the expense of forests, wetlands and other semi-natural ecosystems, contributes to habitat fragmentation and destruction, biodiversity loss and the release of greenhouse gases, which in turn further exacerbates climate change [13,19–22]. Consequently, the agricultural sector is a substantial contributor to global warming. In addition to the ecological consequences, the intensification of land use poses a significant health risk. The presence of persistent pollutants from herbicides in food can result in health complications, including cancer and neurological disorders [23]. The overuse of antibiotics in intensive livestock production has been demonstrated to promote the development of antibiotic resistance, which poses a significant threat to public health [24,25].

As scientific debate has long emphasised, accurate recording and quantification of LUI [26] is essential for the assessment of the impact of intensification on agro-ecological systems, and for the development of sustainable management strategies. In-situ measurements are of central importance, as they provide detailed information directly in the field (e.g. [27–29]. The merits of in-situ measurements are twofold. Firstly, they enable direct observation of complex ecological and agronomic processes. Secondly, they facilitate the capture of locally specific variability that is often not considered in large-scale modelling. This is particularly true in heterogeneous landscapes, where minor variations in soil quality, microclimate or management practices can have substantial consequences for LUI. Consequently, such measurements are imperative. However, in-situ measurements are often time-consuming, costly and have limited spatial coverage, making their large-scale application and continuous monitoring difficult. Moreover, the comparability of results between different regions and studies is problematic due to a lack of standardisation.

RS (RS) has emerged as a key approach to quantify and assess LUI indicators on a large scale, in a timely and standardised manner, and over long periods of time [30,31]. As demonstrated in the works of [32–37] and [38], RS technologies facilitate spectral, spatial and temporal analyses, providing detailed information on vegetation structure, soil condition and other key land cover parameters. Furthermore, RS-based indicators of LUI, including yield estimates, vegetation indices (e.g. NDVI) and soil moisture parameters, which are crucial for the assessment of agro-ecological processes, have been derived for some time. The advent of unmanned aerial vehicles (UAVs) and autonomous robotic platforms, in conjunction with the freely available space-based RS data (Landsat mission [39,40], the Copernicus mission Sentinel [41], and the hyperspectral mission (EnMAP) [42], As demonstrated in the 2015 Copernicus Hyperspectral Imaging Mission (CHIME) [43], the LiDAR mission (GEDI) [44], and in the planned future missions such as the Hyperspectral Infrared Imager Mission (HyspIRI) [45] and the Fluorescence Explorer (FLEX) sensor [46], the derivation of standardised and improved A-LUI indicators will be significantly improved. The substantial body of literature on the derivation of A-LUI indicators using RS is indicative of this phenomenon ([47–50]. As demonstrated in the works of Segarra et al. [51–56] and Hank et al. [38] the subject has been extensively researched.

A promising approach to capture and quantify A-LUI is to understand traits and trait variation of land cover, vegetation and geodiversity [57]. Traits manifest at all spatial and temporal scales, making them ideal for standardised monitoring and the derivation of LUI indicators from local to global levels. All RS technologies record traits and trait variation of vegetation (example [58,59], soil (example [60], terrain and geomorphology (example [61,62] and water (example [63]). RS allows the monitoring of traits and their status, related processes, disturbances or resource limitations in both terrestrial and aquatic ecosystems and their interactions in a timely and standardised manner. Furthermore, RS data that capture traits have the capacity to establish a correlation between the sensitivity of the analysed environmental unit and various globally relevant pressures, including climate change and LUI with its socio-ecological consequences [64]. In addition, novel indicators for quantifying urban LUI have already been developed using RS and the trait approach [65,66]. Yet, to ensure the comparability of data and derived LUI indicators at both local and global scales, it is crucial to develop standardised methods for data collection and analysis. In recent years, there has been an increasing focus at the international level on the establishment of measurement standards. International organisations such as the Food and Agriculture Organization of the United Nations (FAO) and the Intergovernmental Panel on Climate Change (IPCC) promote the establishment of international standards for the measurement and assessment of agricultural intensification across local and global scales. These organisations are increasingly recognising the value of RS and incorporating RS-based indicators into their standards and guidelines.

Nevertheless, the full potential of RS for the development of LUI indicators is still to be unlocked. In order to understand RS-based LUI indicators, derive new ones and assess the suitability of different RS techniques for developing and categorising new indicators, we first need to define and structure these indicators and discuss them in context. We still lack a compendium offering a comprehensive overview of A-LUI indicators that can be derived using RS, so the objectives of this paper are as follows: (I) Definition and compilation of standardised indicators for monitoring A-LUI for Germany, Europe and the world (FAO, OECD, World Bank, EUROSTAT), (II) Compilation of in-situ methods for monitoring LUI, (III) Introduction of a RS based definition of A-LUI by five traits, which are: the trait indicators of A-LUI, the genesis indicators of A-LUI, the structural indicators of A-LUI, the taxonomic indicators of A-LUI and the functional indicators of A-LUI, (IV) Numerous

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examples are used to illustrate the application of RS based on the five traits, (V) Finally, new approaches for quantifying and evaluating A-LUI using RS are presented.

2. Definition, Standards and Programmes for Monitoring the Intensity of Agricultural Land Use

2.1. Definition of A-LUI

Despite the significance of quantifying the urban LUI, the definition remains elusive, as the monitoring of anthropogenic changes and pressures/impacts on agricultural ecosystems/landscapes is a complex and multidimensional phenomenon [67] that is challenging to quantify [33,68]. As Diogo et al. [69] emphasise, the direction of change (positive or negative) of the LUI is also difficult to assess, as it depends on highly context- and scale-dependent processes that vary regionally, have direct and indirect effects on the whole system, and can mutually influence each other (increase or decrease). Conversely, the utilisation of inadequate (one-dimensional) indicators to quantify the LUI has been observed [70]. This is primarily due to the restricted availability of readily available local in-situ data, such as pesticide, fertiliser or machinery use, often due to data protection constraints, and frequently available only in aggregated form within reports. 1) The FAO reference doesn't define "intensity" (the term isn't even used). It describes datasets but is not about their interpretation. 2) Limiting LUI to only the use of inputs is too narrow. In particular in the context of RS. Landscape simplification is another aspect of intensification, and it can actually be well captured by RS. Therefore, we suggest Diego et al. [69] as an important indicator of LUI, which includes the main indicators of management intensity, landscape structure, and agricultural productivity.

2.2. Programmes for Monitoring A-LUI at National, European and Global Scale

One of the main challenges in monitoring LUI is the need to standardise measurement methods and indicators. In order to achieve national and international comparability in the monitoring of LUI, standardised programmes and indicators for the monitoring of A-LUI have been introduced at national (Germany), European and global level. The most important programmes and responsibilities for the monitoring of agricultural LCI for Germany, Europe and the world are listed below.

National scale

Land Register: The land register records the types of land and their use in Germany. It is maintained by the state surveying and land registry offices. Most countries have detailed land register records of land type and ownership, maintained by the state surveying and land registry offices.

- Agricultural Structure Survey: Regular surveys of agricultural land use, yields, livestock, etc. by National Statistical Offices.
- IACS (Integrated Administration and Control System for Management Aid): In agriculture, the IACS system plays a central role in monitoring and managing data such as information on the use of plant protection products, fertiliser data, soil and water data, and yield and production data, as well as environmental and health data. The monitoring and control of IACS data in agriculture is carried out by different institutions and authorities, mainly at regional, national and European level.
- Europe
- Corine: The European Environment Agency (EEA) coordinates various land use monitoring projects, including the production of Corine Land Cover maps.
- Lucas: LUCAS (Land Use/Cover Area Frame Survey) This is a regular statistical survey of land use and land cover in the EU.Copernicus data: Copernicus is the European Earth Observation Programme (ESA) and provides extensive data on land use from satellite data (Sentinel-1-3).
- Farm structure survey datasets (https://ec.europa.eu/eurostat/statistics-explained/index.php?title=Glossary:Farm_structure_survey_(FSS))

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- Agricultural census data (e.g. production, environmental indicators) at national levels and at sub-national levels (NUTS 1, NUTS 2, NUTS3). https://ec.europa.eu/eurostat/web/agriculture/information-data#Agricultural%20production.
- World
- Global Land Cover (GLC): Several international initiatives produce global land cover maps, including projects supported by FAO and the United Nations Environment Programme (UNEP).
- MODIS (Moderate Resolution Imaging Spectroradiometer): An instrument on NASA's Terra and Aqua satellites that provides global data on land cover and land use change.
- Global Land Analysis and Discovery (GLAD): A University of Maryland project to monitor global land use using high-resolution satellite imagery.
- FAO (Food and Agriculture Organisation of the United Nations), OECD (Organisation for Economic Co-operation and Development) and World Bank (World Bank) use indicators to monitor A-LUI worldwide.

Table A1 provides an overview of the main indicators used by FAO, OECD, World Bank and EUROSTAT to monitor A-LUI.

3. Approaches to Monitoring of A-LUI

The monitoring of indicators to measure and assess A-LUI is based on in-situ and RS-based methods (see Figure 1, RS approaches, as a physically based system, capture status and change, but the cause of change may be different. It is therefore necessary to couple both approaches. The trait approach helps us to understand this, as traits are the crucial link between in-situ and RS approaches (see Figure 1).

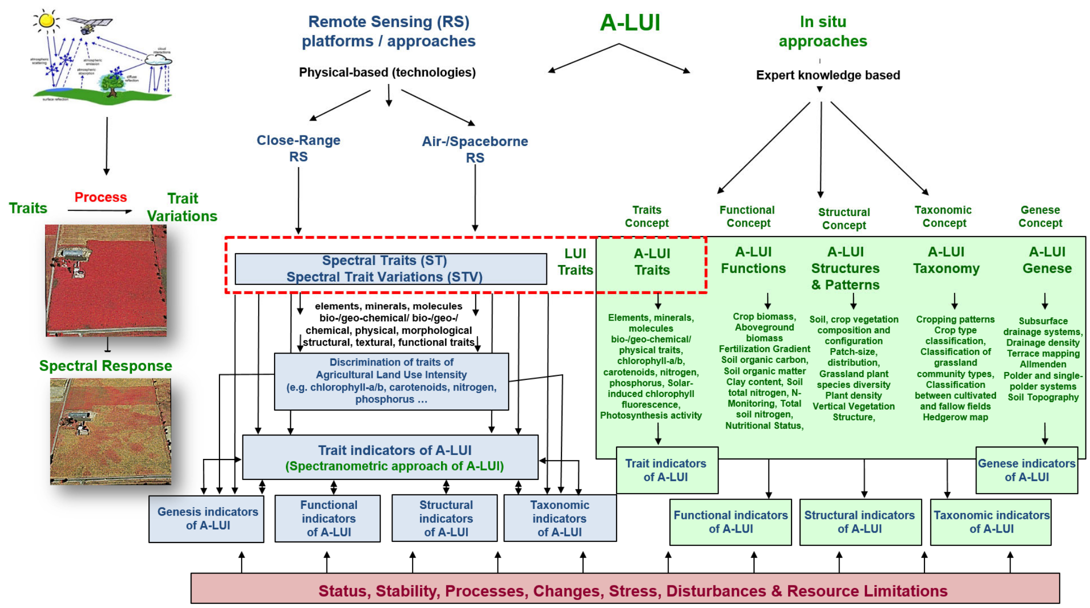

Figure 1. In situ and RS approaches and the five characteristics of agricultural land use intensity (A-LUI) (trait indicators of A-LUI, genesis indicators of A-LUI, functional indicators of A-LUI, structural indicators of A-LUI, taxonomic indicators of A-LUI). Trait indicators of A-LUI are the most important link between in situ and RS monitoring approaches (modified after Lausch et al. [62]).

3.1. In Situ Approaches

The measurement and monitoring of land use intensity represents a pivotal facet of land use research, particularly in the context of sustainable resource utilisation and ecosystem conservation.

In-situ methods have been shown to be a valuable tool for the collection of detailed data and analysis of land use in different geographical and agricultural contexts.

The following observations were made during the course of field studies. One of the fundamental approaches to measuring land use intensity is through direct observation and measurement in situ. These methodological approaches provide direct insights into the environmental and agricultural conditions on the ground. (I) Direct field measurements entail detailed investigations at specific sites where scientists record land use patterns, plant species, soil conditions and other relevant parameters. The methodology encompasses the measurement of plots, the collection of soil and plant samples, and the observation of agricultural practices. Direct measurements are imperative in order to generate accurate data on LUI and to understand the interactions between land use and environmental conditions. (II) Field mapping constitutes a complementary method in which researchers are tasked with the production of maps delineating land use types by traversing the study area on foot or by vehicle. The cartographic representations under consideration here were originally produced on paper or using early graphical systems. They provide a visual representation of the spatial distribution of land use. These data are of pivotal significance for subsequent analysis and interpretation of land use intensity.

Surveys and interviews: In addition to direct field measurements, surveys and interviews represent an integral component of the collection of land use intensity data, as they encompass the human and social aspects of land use. They also record information that only the farmer will know, such as the type and quantity of pesticides used, of fertilizer, etc. Structured interviews and surveys with landowners, farmers and other land users can be used to collect information on land use practices, crop cycles and irrigation methods. The collection of qualitative data facilitates the development of a more profound comprehension of the decision-making processes employed by land users, which are frequently influenced by economic, cultural, and political factors. Cultural and historical studies: The utilisation of cultural and historical studies is instrumental in facilitating a more profound comprehension of the historical evolution of land use patterns. The analysis of historical maps, archival records and government reports provides valuable information on the long-term use and change of land areas and helps to understand trends and shifts in land use.

The disciplines of analogue and digital cartography, as well as Geographic Information Systems (GIS), are discussed herein. The utilisation of mapping technologies and Geographic Information Systems (GIS) is of pivotal significance in the processes of recording and analysing land use intensity. These methodologies provide a comprehensive visual representation of the physical and agricultural traits of an area. Topographic maps: Topographic maps, produced by surveying, provide a basic representation of physical features such as contour lines, land cover and infrastructure. These maps constitute a valuable source of data for spatial analysis of land use. Aerial mapping: Prior to the advent of contemporary satellite technologies, aerial photographs were captured from aircraft and utilised to generate detailed cartographic representations. The interpretation of these images, frequently facilitated by the use of stereoscopes for three-dimensional viewing, enabled precise analysis of land use patterns and changes. The third point of the categorisation is as follows: Geographical Information Systems (GIS) and vector data. Geographic Information Systems (GIS) utilise vector data to display and analyse geo-referenced information on land use types and distributions. These systems facilitate sophisticated spatial analysis and monitoring of LUI indicators at local, national, and global levels.

Collection and analysis of agricultural yield data, as well as the maintenance of administrative records. The analysis of land use intensity is facilitated by quantitative and administrative information, which is provided by agricultural yield data and legal documents. Yield measurements: Yield data, frequently supplied by local or national agricultural authorities, offer insights into the productivity and utilisation of agricultural land. This information is indispensable for drawing conclusions on the intensity and efficiency of land use. Cadastral data: Cadastral data, encompassing land registry records and associated legal documentation, contains information pertaining to land ownership, delineated parcel boundaries and land use rights. These data are of crucial importance

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for the comprehension of formal land use patterns and their legal framework. IACS data: The IACS system occupies a pivotal position in the aggregation and administration of agricultural data within the European Union. The database under consideration encompasses a wide range of data, including but not limited to: information pertaining to plant protection products; fertilisers; soil and water data; yield data; and production data. The systematised nature of these data facilitates the monitoring and evaluation of LUI.

Phenotyping laboratories: Contemporary phenotyping laboratories (e.g. Danforth Plant Science Center, USA; IPK Gatersleben, Germany; JPPC, Germany; International Plant Phenotyping Network) utilise technologies such as automated imaging, sensors, drones and robots to collect substantial data on plant growth, developmental disorders, soil, climate and their interactions under laboratory conditions. This high-throughput phenotyping approach enables researchers to analyse numerous plants expeditiously and efficiently. Phenotyping laboratories are of significant importance in the context of LUI monitoring, as they facilitate the analysis and comprehension of the repercussions that intensive agricultural practices have on both plants and soils. This analysis encompasses the assessment of the impact on plants, including the enhancement of yield and the cultivation of stress resistance, as well as the investigation of the sustainability of land use, encompassing issues such as soil degradation. The following aspects should be monitored: Erosion and nutrient depletion; monitoring resource efficiency (reduced fertiliser use, water-saving irrigation techniques). Analysing biodiversity and ecosystem services (monitoring the genetic diversity of crops and analysing their interaction with the environment (changes in genotype, phenotype, epigenetics). Phenotyping laboratories are particularly well-suited to the testing and development of new sensor systems in a range of realistic and controlled cultivation scenarios (e.g. the FLuorescence EXplorer (FLEX) [71]. The testing of sensor prototypes on different plant species under controlled conditions, such as varying light conditions, temperature and humidity, is a further method of evaluation. For instance, the RS-based indicator of solar-induced chlorophyll fluorescence (SIF) has been the subject of study in phenotyping laboratories, with a view to monitoring plant stress [72]. Moreover, this data is imperative for the validation of novel sensors and the assessment of their measurement accuracy and efficiency.

The implementation of in situ LUI monitoring techniques frequently necessitates a considerable investment of labour, often resulting in protracted monitoring processes. These methodologies are further constrained to specific geographical areas and temporal frames. Nevertheless, they furnish significant insights into land use and LUI, derived from highly accurate local information. These methodologies form the foundation for contemporary, technologically advanced RS technology and data analysis techniques. It is therefore evident that the combination of in-situ and RS approaches is imperative for effective LUI monitoring.

3.2. Remote Sensing Approach

3.2.1. Principles of Recording A-LUI Using RS

All RS technologies are non-contact and detect traits and trait variations of land cover from a few millimetres (close range) to thousands (air-spaceborne) of kilometres (see Figure 2). RS sensors are integrated on various RS platforms such as wireless sensor networks (WSN), laboratory and field platforms, lysimeters (soil), pheno cameras, masts, drones, balloons, as well as air- and spaceborne platforms (see Figure 2). Different RS technologies (RGB/photographic, multispectral, hyperspectral, TIR, laser, radio/RADAR and LiDAR) are often used in combination on many platforms. As traits and trait variations exist from local to global, RS allows objective and continuous monitoring and derivation of standardised LUI indicators from local to global scale.

The collection of indicators that quantify A-LUI is a crucial RS application that began with the availability of spaceborne RS data in the 1970s [73]. The focus here was on land cover monitoring, LULC and crop classifications, land use change [73,74] and the determination of basic functional vegetation traits using indicators such as NDVI [75]. The free availability and opening up of RS missions (such as Landsat [76], the Copernicus missions [77] or the hyperspectral mission (EnMAP,

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[42] accelerated the use and development of further RS-based LUI indicators. RS approaches are certainly ideal for deriving A-LUI indicators, as RS is based on the following basic principle: RS captures traits and triat variations directly or indirectly of plants, vegetation diversity, geodiversity, geomorphology, terrain and water diversity. The spectral reflectance and absorption of pixels are thus the result of interactions between light (the atmosphere), phylogenetic/genetic, biophysical, biochemical, physical, morphological, physiological, phenotypic, structural, taxonomic and functional characteristics of the recorded traits of vegetation diversity, geodiversity [12,78] and anthropogenic changes and disturbances by LUI. RS-based monitoring can thus capture indicators of LUI, as LUI is subject to complex and multidimensional influences, which are characterised by the interaction of abiotic - biotic compartments and anthropogenic factors (e.g. pesticide use, fertilisation, management) and their interactions.

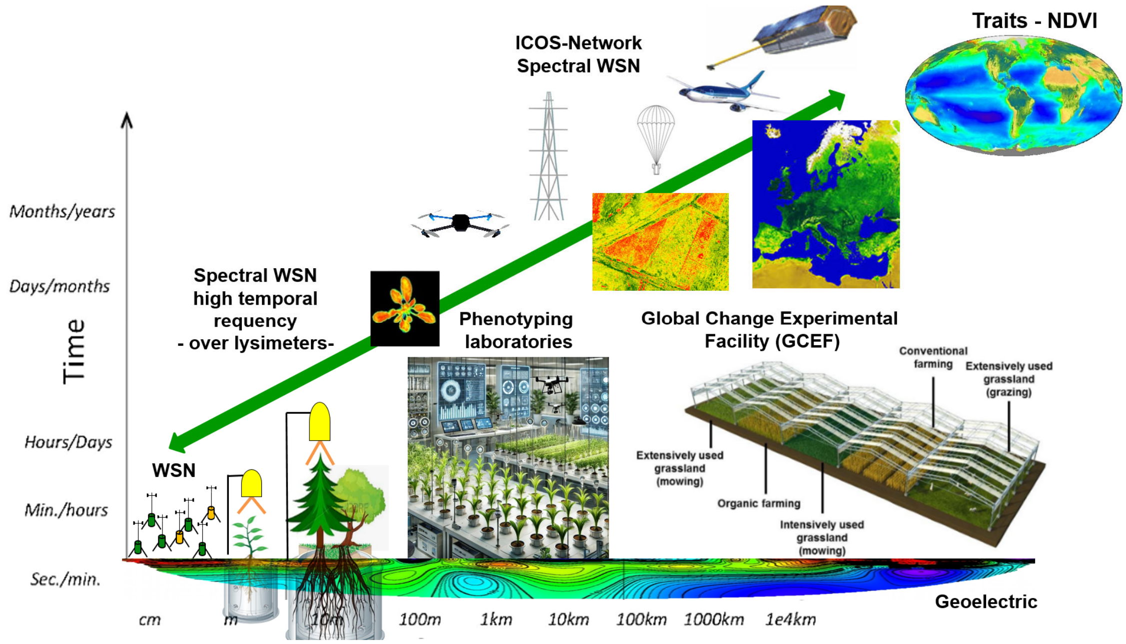

Figure 2. Different RS platforms; wireless sensor networks (WSN); WSN over lysimeters, Phenotyping laboratories, Global change Experimental Facility (GCEF), Drones, Towers, Balons, airborne-and spaceborne RS platforms withand differnet RS technologies (RGB/photography, multispectral, hyperspectral, thermal, laser, RADAR, acoustic and LiDAR) to monitor indicators of land use intensity on different spatial and temporal scales (modified from Lausch et al. [63]).

3.2.2. Challenges of Recording A-LUI Using RS

The recording of A-LUI through RS brings numerous advantages, but also specific challenges associated with the particularities of agricultural practices and sensor characteristics (spectral, spatial, temporal). For example, Maudet et al. [79] clearly emphasised in a comparative study that there are significant differences between in-situ indicators and land use data derived from RS. They demonstrated that land cover maps based on RS are not a reliable indicator of management intensity at the field level, as the classifications of these maps do not adequately capture the A-LUI caused by agricultural practices. In addition, the landscape structure described by the area diversity varies significantly depending on the classification systems used. These differences strongly depend on the number of intensity classes considered, which we analysed with regard to the sensitivity of a target variable [79]. The following challenges exist when deriving A-LUI from RS data:

(1) Limited coverage of agricultural practices

RS can identify different agricultural crops, but differentiating between intensive and extensive cultivation (e.g. conventional vs. organic farming, monocultures vs. crop rotation) is still a challenge.

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Spectral indices such as the NDVI only provide information on vegetation density and health, but not directly on the intensity of use, such as the use of fertilisers, pesticides or irrigation systems. In order to record the use of fertilisers, pesticides or irrigation systems using RS, this is often done using indirect indicators or a set of indicators

Recording management practices: The way agricultural land is managed, such as the frequency of ploughing, crop rotation or the use of agrochemicals, is crucial for LUI. These management practices can only be derived from RS data with a high geometric resolution (< 1m).

(2) Seasonal dynamics

Agricultural areas go through different phases within a year (sowing, growth, harvest, fallow), which lead to significant changes in the vegetation. These seasonal variations can lead to misjudgements of the LUI if sufficient high-resolution, temporally dense data is not available. The challenge is to distinguish between natural seasonal variations and actual intensity changes. Multiple harvests: In regions with several harvests per year (e.g. in tropical areas), repeated RS images are required to correctly record the number and intensity of harvests. However, the temporal coverage of satellite images is often insufficient to fully document such multiple harvests. The use of RADAR data (Sentinel 1) in combination with optical RS data is expedient here, as they are recorded independently of cloud cover and at a high temporal density.

(3) Irrigation and water management

Irrigation is a central factor of LUI, but the detection of irrigation systems is only indirectly possible through RS, e.g. by quantifying soil moisture or vegetation health. Especially in regions with periodic rainfall, it is difficult to distinguish between naturally occurring moisture changes and human-induced irrigation. Recognising water stress: RS can indicate the condition of vegetation, but it is often difficult to distinguish between natural causes (e.g. drought, inadequate soil properties) and the effect of intensive irrigation practices or water stress.

(4) Fertiliser and pesticide use

The use of fertilisers and pesticides is a key factor in the intensity of agricultural production, but these inputs are virtually invisible to RS. While it is possible to infer the impact of these inputs on vegetation health (e.g. via spectral indices), there is no direct evidence of the amount or type of chemicals used.

Long-term soil degradation: Intensive use of fertilisers can have long-term effects on the soil, such as salinisation or nutrient depletion, but these are difficult to detect by RS. These effects are not directly reflected in the vegetation indices.

(5) Small-scale agricultural structures

In many parts of the world, particularly in developing countries, agriculture is small-scale and heterogeneous. Small farmers often cultivate very small plots of land with different utilisation intensities. As a result, there are numerous problems with the demarcation of field boundaries using RS. For example, different plant species or land use types can have similar spectral signatures, which makes differentiation difficult. Furthermore, natural field boundaries are often not sharp, e.g. due to transition zones or hedges, which makes precise demarcation difficult. The spatial resolution of many RS data is often not sufficient to reliably capture these small-scale differences. High-resolution RS data (< 1m) is required here, but this is often expensive or not regularly available. For example, Landsat or Sentinel 2 data cannot be used to determine roads, field paths or small structures [80] , which is crucial for deriving field structures. Furthermore, Figure 3 shows the problems of the spatial resolution of RS data in the detection of crop vegetation using the example of an oilseed rape plant, which was recorded at different flight altitudes (1m-80m). There are currently only a few RS-based sensors that are freely available and can quantify high-resolution landscape structures and patterns (e.g. detection of agricultural utilisation boundaries, small structures) with sufficient spatial accuracy (see Table 2A). In order to record the small-scale nature and utilisation structure, aerial image data (spatial resolution of 20 cm) is therefore repeatedly used, which is subsequently recorded vectorially and/or manually [81–84].

(6) Agroforestry and mixed cropping:

In agroforestry systems or mixed cropping, it is difficult to derive the intensity of agricultural use from RS, as the different plant species are intertwined and are often grown under trees. Tree canopies can obscure the underplanting, so that important information about the agricultural intensity is lost.

(7) Limited spectral information of RS data

While standard satellite sensors such as Landsat or Sentinel provide useful spectral information, these are often insufficient to capture subtle differences in the type and intensity of agricultural use. Hyperspectral RS sensors (e.g. EnMAP, DESIS) could provide more detailed information, but in many cases they are not widely available and their spatial resolution is limited to at least 30x30m.

Vegetation indices are often insufficient: spectral indices such as the NDVI can capture general biomass and vegetation health, but they do not provide detailed information on the intensity of agricultural activities (e.g. distinction between intensive and extensive cultivation).

(8) Climatic and topographical influences

Weather events such as drought or flooding influence vegetation development and can make it difficult to separate differences in LUI from natural or climate-related influences. Topography and land cover: In hilly or mountainous regions and in areas with widely varying land cover (e.g. grassland and arable land next to each other), RS data may have difficulty providing accurate LUI data, as topography or shading may affect the quality of the data.

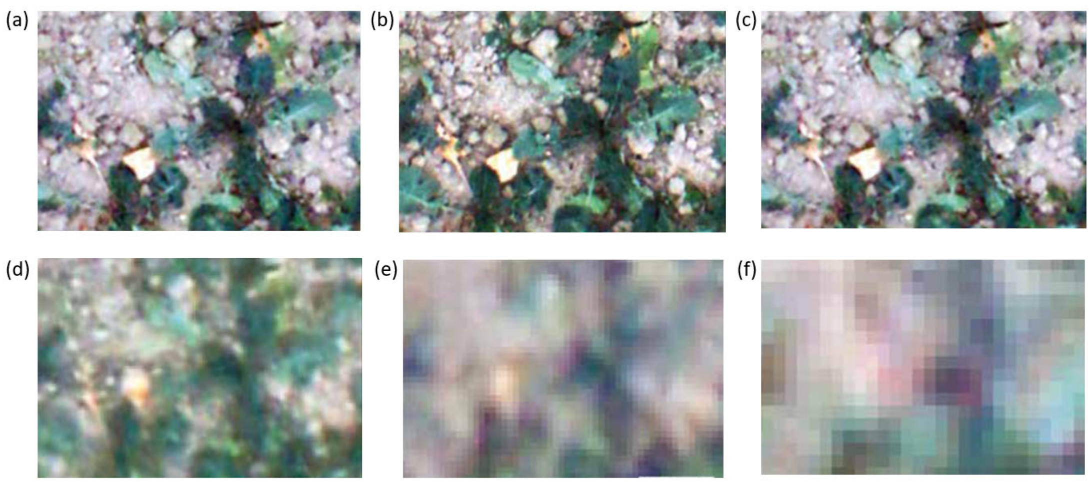

Figure 3. Problems of spatial resolution of RS data in the detection of crop vegetation, (a) Image of a rapeseed plant at a flight altitude of 1 m with a ground resolution of 0.6 mm per pixel. (b) Image of a rapeseed plant at a flight altitude of 5 m with a ground resolution of 1.5 mm per pixel. (c) Image of a rapeseed plant at a flight altitude of 10 m with a ground resolution of 2.5 mm per pixel. (d) Image of a rapeseed plant at a flight altitude of 20 m with a ground resolution of 5 mm per pixel. (e) Image of a rapeseed plant at a flight altitude of 40 m with a ground resolution of 10 mm per pixel. (f) Image of a rapeseed plant at a flight altitude of 80 m with a ground resolution of 20 mm per pixel (from Grenzdörffer, (Grenzdörffer, G., 2022. Grundlagen der landwirtschaftlichen Fernerkundung https://www.ktbl.de/fileadmin/user_upload/Artikel/Pflanzenbau/Drohnenfernerkundung/Drohnenfernerkundung.pdf.).

4. Definition of A-LUI Using RS

In order to understand RS-based A-LUI indicators, to derive new ones and to understand the suitability of different RS technologies with regard to the development and categorisation of new indicators, a definition of LUI using RS data is required. LUI and their indicators can be described by its five characteristics, namely (see Figure 4): (I) the trait indicators of LUI, (II) the genesis indicators of LUI, (III) the structural indicators of LUI, (IV)) the taxonomic indicators of LUI, and (V) the functional indicators of LUI (modified after Lausch et al.[61] . These five characteristics of LUI exist on all spatial and temporal scales and can be defined as follows (modified after Lausch et al. [62]).

(I) **The trait indicators of LUI**, which represents the diversity of the biochemical-, physical, optical, morphological-, structural-, textural- and functional characteristics of LUI traits that affect, interact with or are influenced by their genese-, taxonomic-, structural- and functional LUI indicators;

(II) **The genesis indicators of LUI**, which refers to the diversity of the length of evolutionary pathways associated with a particular set of LUI traits, taxa, structures and functions of LUI diversity. Therefore, groups of LUI traits, LUI taxa, LUI structures and LUI functions that maximise the accumulation of functional diversity of LUI diversity are identified;

(III) **The structural indicators of LUI**, namely, the diversity of the composition and configuration of LUI characteristics;

(IV) **The taxonomic indicators of LUI**, representing the diversity of LUI components that differ from a taxonomic perspective;

(V) **The functional indicators of LUI**, which is the diversity of LUI functions and processes, as well as their intra- and interspecific interactions.

A clear distinction and attribution of the five characteristics of LUI diversity monitored through RS is not always achievable. However, such differentiation remains valuable for tracking, categorising, and evaluating various LUI indicators derived from RS, and for enhancing the understanding of the connections between in-situ and RS methodologies .[61].

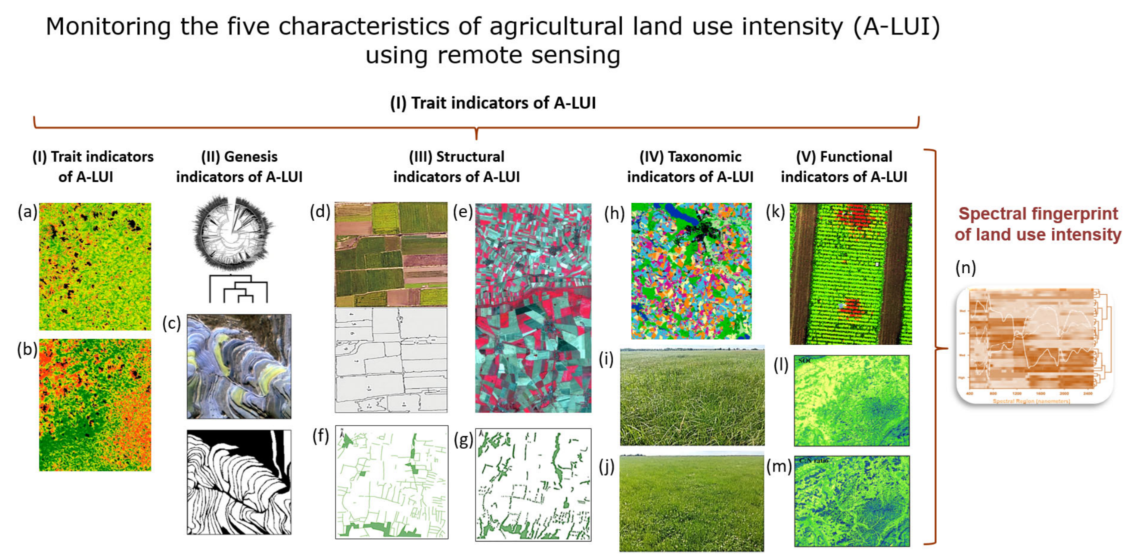

Figure 4. RS monitoring of the five characteristics of agrariultural LUI (A-LUI), (I) the trait indicators of A-LUI, (II) the genesis indicators of A-LUI, (III) the structural indicators of A-LUI, (IV)) the taxonomic indicators of A-LUI, and (V) the functional indicators of A-LUI. (a) Chlorophyll value, (b) phosphorus value, (c) terrace detection, (d) perimeter boundaries of farmland blocks, (e) shape, size and small-scale nature of the border between Saxony-Anhalt and Lower Saxony, (f) hedgerow map classifications from an aerial photography and (g) TerraSAR-X image, (h) wall-to-wall crop type mapping using the bendchmark 10-day interval composite of Landsat and Sentinel-2 time series, types of grassland management intensity at the Podlaskie study sites, (i) extensive, (j) intensive, (k) disease severity prediction in sugar beet using UAV multispectral data, (l) mean SOC content and (m) C:N ratio maps predicted with Sentinel 1, Sentinel-2 and Landsat-8 data (modified after Lausch et al. [63]).

4.1. Monitoring the Trait Indicators of A-LUI Using RS

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"The trait indicators of LUI, which represents the diversity of the biochemical-, physical, optical, morphological-, structural-, textural- and functional characteristics of LUI traits that affect, interact with or are influenced by their genese-, taxonomic-, structural- and functional LUI indicators" (modified after Lausch et al. [62] (see chapter 4.).

The recording and monitoring of traits form the basis for monitoring the genetic, taxonomic, structural and functional LUI indicators of the LUI indicators using RS [85,86]. The monitoring of traits and trait variations (vegetation, soil, geomorphology, water) is therefore an essential basis for the assessment and management of agricultural land use intensity (LUI) using RS. Traits are plant, soil and hydrological properties that represent indicators of agricultural processes and their intensity. The targeted monitoring of such traits makes it possible to use resource inputs such as fertilisers, water and pesticides more efficiently and thus to make agricultural production more sustainable. The LUI traits refer directly to the extent of technological progress, the precision of the control of the resources used and increases in efficiency in agriculture. The more precisely plant and soil-related traits such as growth, yield, resistance to stress factors or nutrient uptake can be monitored, the more effectively land use intensity can be controlled and optimised. Table 3A contains numerous examples, sensors and references.

4.1.1. Trait Indicators of A-LUI - Spectranometric Approach

A particularly suitable approach for recording A-LUI is the spectranometric approach according to Greg Asner [86]. This method utilises e.g. hyperspectral and multispectral RS data, which enables a detailed and direct recording of biochemical and structural characteristics of the vegetation (see Figure 5). The approach is characterised by several specific strengths: The method allows a detailed biochemical, structural and functional characterisation of vegetation traits. Chemical characteristics such as nitrogen and chlorophyll content as well as concentrations of lignin, cellulose and water content are precisely quantified using RS. As intensive agricultural use is typically associated with increased use of nitrogen fertilisers and pesticides, the resulting biochemical changes in the vegetation can be precisely recorded and spatially mapped. The hyperspectral approach allows precise quantification of plant structural characteristics such as leaf area index (LAI), leaf angle distribution, plant height and biomass. These parameters are directly dependent on the type and intensity of cultivation, so that direct conclusions can be drawn about the intensity of land use. This method monitors the early detection of functional characteristics such as plant stress, for example caused by water scarcity, over-fertilisation or pest infestation. The detailed spectral signatures make stress symptoms visible at an early stage so that management decisions can be adapted and optimised in good time. By using hyperspectral RS technologies, which capture hundreds of narrow spectral bands, changes in plant physiology and soil can be measured and quantified in a differentiated manner. This allows a precise characterisation of the intensity of use at both field and landscape level. Finally, the spectranometric approach integrates hyperspectral data with ecological and agronomic models as well as satellite data from missions such as FLEX or Sentinel-3, enabling validated, precise and in-depth statements about vegetation processes and the intensity of land use. The scientific significance of Greg Asner's approach lies in particular in making complex ecological relationships such as biodiversity, carbon storage and the effects of human activities on ecosystems comprehensible in detail. In the agricultural context, this enables a better understanding of sustainability and the ecological effects of different land use strategies. To summarise, the spectranometric approach offers a comprehensive, high-resolution and differentiated method for the precise recording of agricultural land use intensity and thus represents an important basis for sustainable agricultural practices. Specific examples of monitoring the trait LUI indicators are as follows:

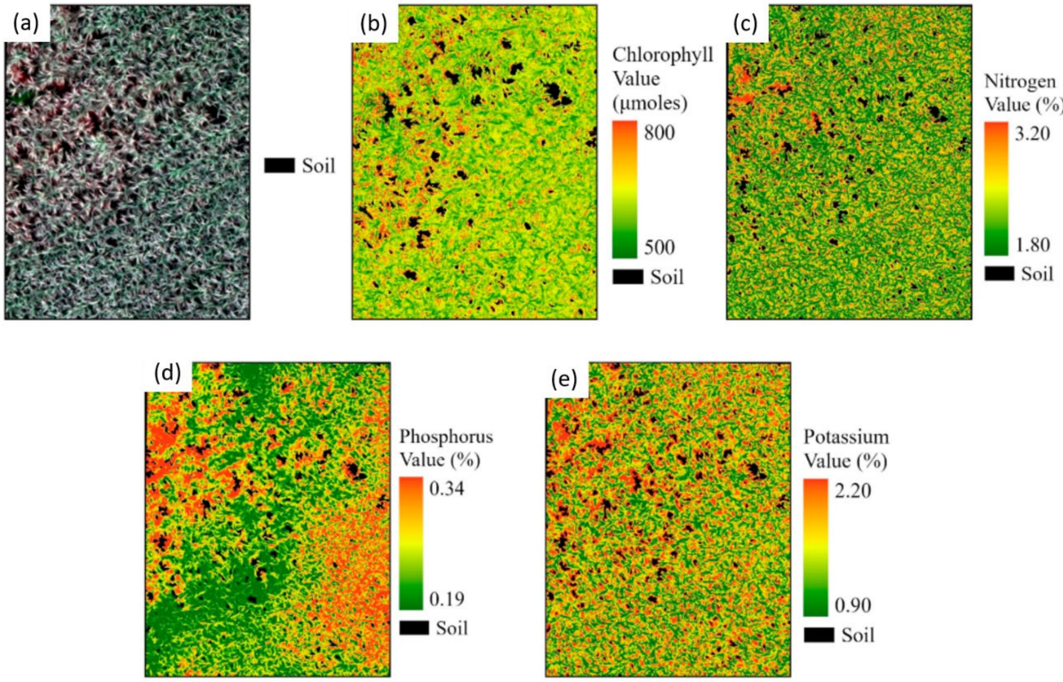

Figure 5. Mapping spatial nutritional variability of (a) sugarcane (b) foliar chlorophyll, (c) foliar Nitrogen, (d) phosphorus, (e) potassium concentrations using a MicaSense RedEdge-P camera attached to a drone and LiDAR data (from Picado and Romero [87]).

4.1.2. Trait Indicators of A-LUI - Chlorophyll Content

The measurement of chlorophyll content (Cab) using RS technology is of central importance, as this parameter is closely correlated with photosynthetic performance and thus plant vitality and productivity [88]. Chlorophyll serves as an effective indicator of LUI, as it reflects the influence of agricultural practices, fertiliser use and plant health. Higher anthropogenic interventions, for example through intensive fertilisation or the use of pesticides and precision agriculture, are directly reflected in changes in chlorophyll levels. An increased chlorophyll content often signals improved plant vitality, while stress factors such as drought, disease or nutrient deficiency can lead to a reduction in chlorophyll content. However, intensive management methods, including targeted plant protection measures, can partially compensate for such stress factors, which in turn results in more stable chlorophyll levels [88]. The importance of chlorophyll content arises from its role as an essential ecophysiological variable, which is closely linked to photosynthetic activity and thus to the vitality and productivity of plants [89]. In particular, the chlorophyll content provides information about nitrogen uptake and the general nutritional status of the vegetation. Plants in intensive farming show higher chlorophyll levels due to a higher nitrogen supply, whereas extensive or less intensively farmed systems typically have lower chlorophyll concentrations [90].

Hyperspectral RS techniques, which are characterised by their high spectral resolution and sensitivity to biophysical parameters, are primarily used for RS of chlorophyll content [89] (see Figure 6). Current and future hyperspectral missions such as PRISMA [91] , HISUI [92] , SHALOM[93], CHIME [43] or EnMAP [42] and others enable the acquisition of detailed spectral signatures, which form the basis for a precise estimation of the chlorophyll content. The Copernicus Hyperspectral Imaging Mission (CHIME) of the European Space Agency (ESA) in particular, with a spatial resolution of 20 to 30 metres and a temporal repetition cycle of around 10-12 days, opens up new perspectives for monitoring chlorophyll content in agricultural contexts [43,88]. There are two main traditional approaches to determine chlorophyll content by RS: empirical regression techniques and physically based modelling approaches. Empirical techniques usually use spectral indices calibrated to field measurements, but often show site-specific and vegetation-dependent limited transferability

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[94]. Physically based models, on the other hand, which are based on radiative transfer models (RTMs), are more robust and transferable, but require complex calibration and are computationally intensive [90,95]. More recently, the hybrid approach has become established, which combines physical models with machine learning and thus unites the advantages of both methods: the robustness of physical models and the efficiency of machine learning methods. Especially in combination with active learning techniques, this approach shows promising results in chlorophyll estimation and other vegetation parameters [88,89]. Despite the progress, challenges remain, such as spectral saturation effects at high chlorophyll levels or interference from ground reflections in open vegetation stands. In addition, the relationship between chlorophyll and nitrogen content can vary from species to species, which makes it difficult to apply universal models [96]. Therefore, hybrid approaches combining physical and data-driven methods are currently the most promising way to improve chlorophyll estimation by RS and ensure more precise monitoring of plant condition and nitrogen uptake in agriculture.

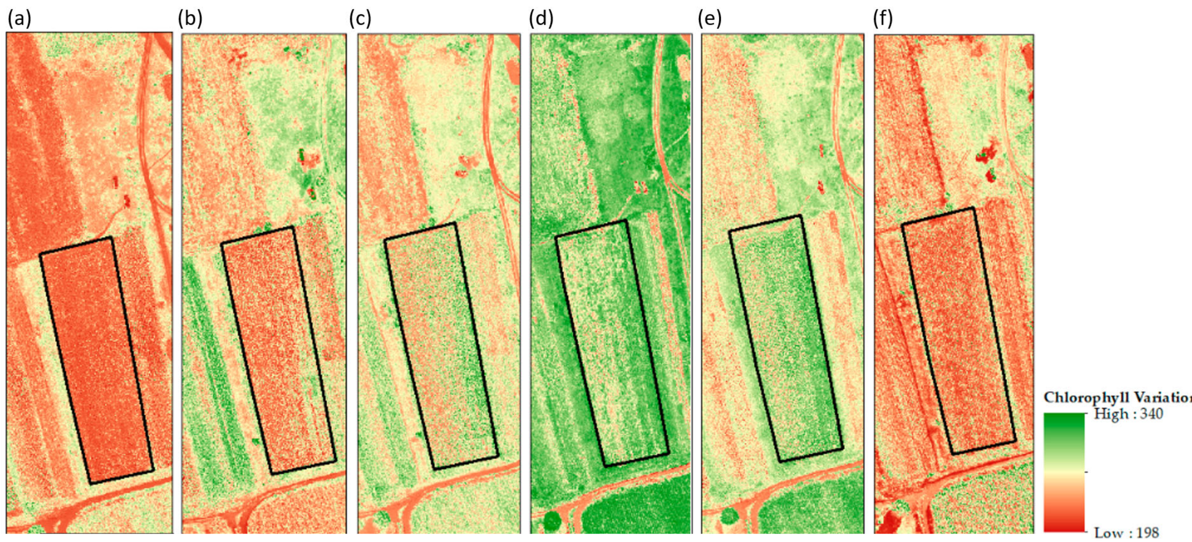

Figure 6. Spatial distribution of chlorophyll content over the maize field for vegetative stages based on UAV-MS data, (a) early vegetation, (b) mid vegetation, (c) late vegetation, (d) early reproductive, (e) mid reproductive, (f) late reproductive (from Brewer et al. [97]).

4.1.3. Trait Indicators of A-LUI - Chlorophyll Fluorescence

The Fluorescence Explorer (FLEX) sensor of the European Space Agency (ESA) [98] offers outstanding potential for the precise measurement of agricultural land use intensity (LUI) (see Figure 7). By directly measuring solar-induced chlorophyll fluorescence (SIF), FLEX provides profound insights into the photosynthetic activity, vegetation health and productivity of agricultural land [72,99]. The methodological suitability of FLEX for the assessment of agricultural land use intensity is based on several crucial factors: Firstly, FLEX directly measures photosynthetic activity, as SIF directly correlates with the photosynthetic rate of vegetation. Intensively used agricultural areas, characterised by increased use of fertilisers, irrigation and pesticides, typically have higher fluorescence values, making FLEX a reliable tool for assessing LUI [72] . Secondly, the FLEX sensor allows early detection of plant stress, for example caused by drought, nutrient deficiency or over-fertilisation [100]. This early detection makes it possible to initiate targeted management measures before visible damage or significant yield losses occur[72]. Thirdly, with the FLORIS instrument (Fluorescence Imaging Spectrometer), FLEX has a high spectral and spatial resolution, which means that subtle differences in photosynthetic performance between intensively farmed areas can be precisely recorded. The spatial resolution of around 300 metres allows detailed analyses and differentiated interpretations of land use intensity at a regional level [98]. Another methodological

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advantage is the integration of FLEX with Sentinel-3 satellite data. The synergetic use of optical and thermal sensors significantly improves the accuracy of deriving vegetation-relevant parameters such as leaf area index (LAI) and chlorophyll content. These parameters are essential for the comprehensive assessment of vegetation health and enable a differentiated assessment of agricultural utilisation intensity [99]. In addition, FLEX contributes significantly to the quantification of plant carbon sequestration, as SIF is closely linked to carbon uptake and thus to the global carbon cycle. This information is not only relevant for agricultural issues, but also provides important insights for global climate modelling and sustainable development concepts [101].

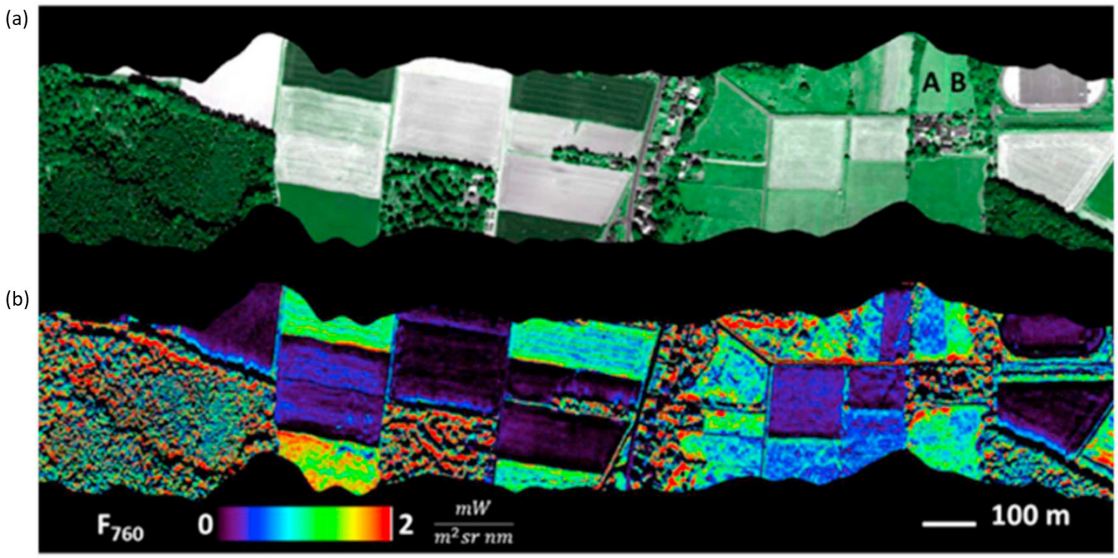

Figure 7. (a) Reflectance and canopy SIF (b) maps obtained with the HyPlant airborne sensor over an agricultural research site in Klein Altendorf, Germany. Lower SIF is evident in forests (left in lower panel) and higher SIF in dense agricultural fields (middle and right in lower panel). Fluorescence emission reveals information on vegetation status which is not visible in the reflectance domain. For example, the two fields denoted as A and B display almost identical reflectance (b), whereas their fluorescence emission is very different (a) (from Mohammed et al. [72]).

4.1.4. Trait Indicators of A-LUI - Leaf Nitrogen Content

The monitoring of leaf nitrogen (Leaf Nitrogen, LN, Leaf Nitrogen Content, LNC) as an indicator of A-LUI, provides important insights into the relationship between agricultural practices and plant physiology. Leaf nitrogen is an essential component of plant protein metabolism and plays a central role in photosynthesis. Intensively farmed agricultural areas, which are often characterised by increased use of fertilisers, generally have higher leaf nitrogen concentrations. This increased nitrogen availability promotes plant growth and increases productivity. A study by Dong et al [102] emphasises that the allocation of nitrogen in leaf structures, especially in cell walls, increases with leaf mass per area (LMA), which indicates the importance of structural and metabolic components of leaf nitrogen. The intensity of land use influences not only the leaf nitrogen content, but also the biodiversity of agroecosystems.

RS technologies have proven to be effective tools to measure LNC non-invasively and over large areas. There are a number of review studies on the detection of leaf nitrogen using RS technologies on different platforms [103–109]. Hyperspectral RS captures reflectance spectra of vegetation over a broad wavelength spectrum, which enables detailed analysis of leaf biochemistry. A study by Berger et al. [90] developed a hybrid method for estimating the aboveground nitrogen content of plants that combines physically based models with machine learning. This method identified specific

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wavelengths in the shortwave infrared (SWIR) range that are particularly relevant for nitrogen detection [90]. The use of hyperspectral RS technology opens up enormous potential for detecting the biochemical constitution of plant traits like the leaf nutrient content. For example, studies use hyperspectral technologies such as EnMap [110], or Prisma[111]) to record the leaf nitrogen content. The use of UAVs RS technologies [112] in combination with advanced machine learning algorithms has increased the precision of LNC estimation. Zhang et al.[113] developed a self-supervised spectral-spatial transformer network using UAV imagery to accurately predict the nitrogen status of wheat fields. This model achieved high accuracy (0.96) and showed good generalisability for nitrogen status estimation[113]. Vegetation indices, such as the Normalised Difference Vegetation Index (NDVI), have traditionally been used to estimate LNC. However, more recent studies have developed more specific indices that are more sensitive to nitrogen variation. A study on estimating leaf nitrogen content in rice using vegetation indices emphasised the role of UAV-based RS in accurately determining nitrogen status at the field level [114] . The combination of different RS platforms, such as satellite imagery and UAVs, enables scalable and flexible monitoring of LNC. A comprehensive analysis of RS monitoring of nitrogen levels in rice and wheat crops over the last 20 years highlighted the importance of integrating different platforms to improve the accuracy and efficiency of nitrogen monitoring [103]. Traditional RS methods to determine leaf nitrogen (leaf N) content are usually based on indirect indicators, such as vegetation indices or chlorophyll-a+-b (Cab) content. However, these approaches reach their limits as the relationship between Cab and leaf N saturates at higher values and they are not very sensitive to early nutrient deficiency. A study by Y. Wang et al. [112] used Sentinel-2 satellite images to estimate various plant biochemical traits in large almond orchards in a two-year study. The traits, including leaf dry mass, leaf water content and leaf Cab, were derived using a radiative transfer model and used to explain the observed variability in leaf N. The resulting Sentinel-2 model for leaf N prediction showed high accuracy with an r^2 of 0.82 and an nRMSE of 13 %. Both the model performance and the contributing traits proved to be stable over the entire two-year period. The integration of these plant biochemical traits thus provides a more reliable and stable basis for leaf N prediction than conventional approaches, opening up promising prospects for application in precision agriculture (see Figure 8).

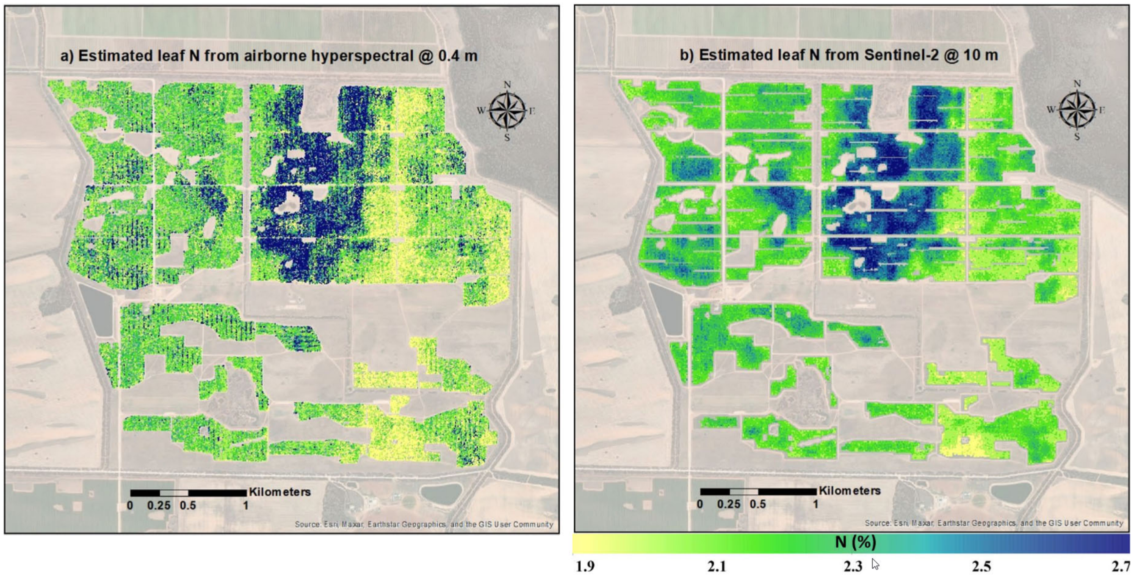

Figure 8. Estimated leaf N maps for the 2021 pre-harvest season based on models (a) airborne hyperspectral-derived Cab and SIF from tree crowns, and (b) Sentinel-2-derived plant traits Cab, Cw, and Cdm. (from Wang et al., [112]).

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4.2. *Monitoring the Genesis Indicators of A-LUI with RS*

The genesis indicators of LUI, which refers to the diversity of the length of evolutionary pathways associated with a particular set of LUI traits, taxa, structures and functions of LUI diversity. Therefore, groups of LUI traits, LUI taxa, LUI structures and LUI functions that maximise the accumulation of functional diversity of LUI diversity are identified (modified after Lausch et al. [62] (see chapter 4). Table 3A contains numerous examples, sensors and references.

4.2.1. Genesis Indicators of A-LUI - Subsurface Drainage

Subsurface drainage (DS) systems play an essential role in modern agriculture by efficiently draining excess water, thereby improving soil quality and agricultural productivity. Accurately locating and analysing these systems is crucial for sustainable land management, as unmapped drainage systems can lead to water quality degradation and increased nutrient inputs into water bodies [115]. Over the centuries, various civilisations such as the Egyptians, Chinese and Indians developed their own drainage systems. In Europe, the drainage of agricultural land was established in the 17th century [116] . With the advent of motorised machinery in the 20th century, underground drainage systems spread rapidly, expanding agricultural land and making previously wet areas suitable for arable farming [117]. It is estimated that between 54% and 87% of the world's wetlands have been lost since 1700 AD [118]. In addition to their positive effects on agricultural production, drainage systems also have undesirable side effects. They can accelerate the release of nutrients, especially nitrogen and phosphorus, into water bodies and thus increase the risk of eutrophication [115] . In addition, draining carbon-rich wetlands can lead to increased CO2 emissions [119].

RS offer an efficient alternative to time-consuming manual investigations using ground penetrating RADAR and electromagnetic induction and enable large-area detection of drainage systems [120,121] (see Figure 9). The first attempts to record underground drainage systems using airborne thermal infrared images were made as early as the 1970s [122]. Multispectral and hyperspectral imaging utilises near infrared (NIR) and short wave infrared radiation (SWIR) to detect soil moisture. Vegetation indices such as NDVI and NDWI help to identify wet areas where drainage systems may not be working effectively [123] . RADAR RS such as Sentinel-1 enable the detection of soil moisture differences and help to recognise drainage patterns, even under cloudy skies or at night [124]. High-resolution digital terrain models (DTM/DEM) based on LiDAR RS Data help to analyse natural and artificial drainage paths. LIDAR can also detect microtopographies that indicate inadequate drainage [125]. Moist or water-saturated soils have different temperatures than dry soils. Thermal infrared images (TIR), for example from Landsat 8, can be used to recognise drainage, especially after precipitation or at night [126,127]. Studies have shown that the combination of optical and thermal images can significantly increase detection accuracy [128].

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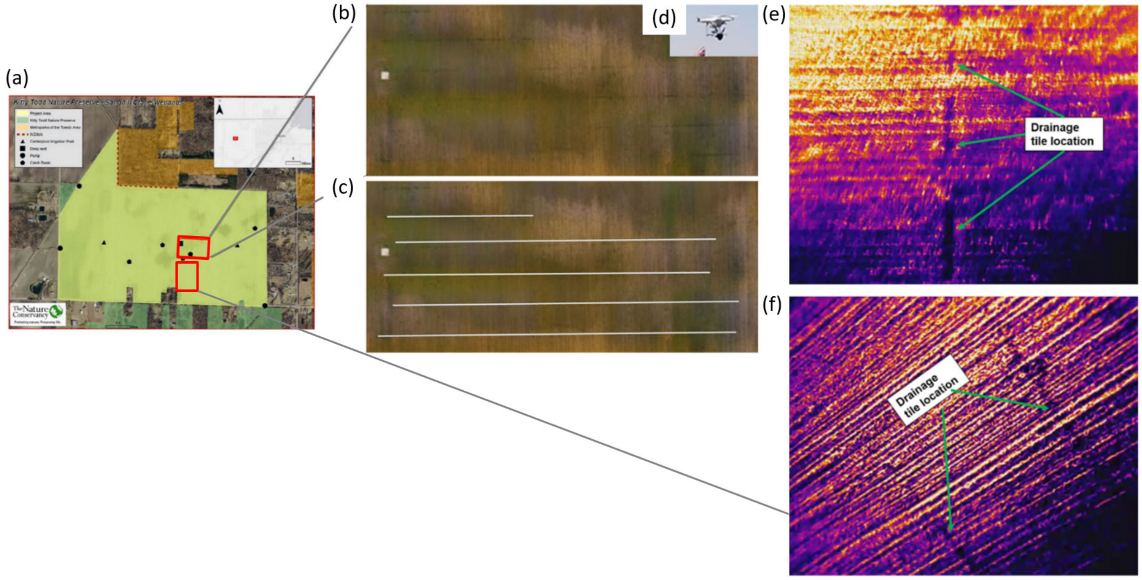

Figure 9. (a) Location of the study site within the Aak Openings regions in Ohio, USA. (b,c) section of visible image with dull color linear feature interpreted as drainage tile with a parallel network, d) the UAV used to acquire image, (e,f) a section of thermal infrared images of the study site with drainage tile (from Becker et al., [128]).

4.2.2. Genesis Indicators of A-LUI - Terrace Mapping

Terrace fields are an important indicator for the genesis of LUI (Land Use Intensity) because they reflect the long-term adaptation and transformation of the landscape by humans. Here are some key reasons. Terraces were built to intensify the cultivation of slopes and to minimise soil erosion. These cultivation terraces are often found in steep, mountainous regions.

In the study by Liu et al. [129], RS data (Sentinel-1/2) was used as an efficient alternative for recording terrace structures, as it enables large-scale monitoring. However, optical satellite images, especially in mountainous regions, are affected by high cloud cover and varying vegetation cover, which makes precise detection of terrace fields difficult. Previous studies on automated terrace mapping using high-resolution satellite imagery, such as the GF-2 satellite mission or WorldView-1/3, have focussed primarily on the Loess Plateau in China, a region with comparatively less topographical challenges [130–132] (see Figure 10.). This work mainly utilised optical RS data and applied object-oriented or deep learning methods for classification [133]. The use of high-resolution satellite images and digital terrain models (DEM) with an accuracy of 1-2 metres significantly improves the recognition accuracy of terrace structures. However, these methods are limited for large-scale analyses due to high costs and a considerable volume of data [129] . Especially in mountainous regions, such as the analysed landscape in southwest China, there are still significant challenges in RS of terraces. Complex planting patterns, including crop rotation and mixed cropping, make it difficult to clearly identify terraces due to spectral similarities between different land cover classes [134]. In addition, low to medium resolution satellite images have a limited ability to detect small-scale terrace structures, as these often only appear as mixed pixels in heterogeneous landscapes [135]. LiDAR (Light Detection and Ranging) and RADAR (Radio Detection and Ranging) are key RS technologies for the detailed detection of terrace structures. They provide precise topographical information that is essential for analysing and managing such landscapes. LiDAR in particular enables the creation of high-resolution, three-dimensional terrain models, which allow reliable mapping of terrace structures even in densely forested areas [136].

An example of the application of this technology is provided by the study by Le Vot et al. [137], which aims to reconstruct the historical development of land use on terraces. The aim of this study is to test the hypothesis of the resilience of these landscapes in the period from the 17th to the 21st

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century. For this purpose, current and archived geodata sets as well as LiDAR-based digital terrain models with a resolution of 1 metre were used. The analysis was carried out in an area that was recently affected by an extreme event and whose reconstruction was considered a challenge. The results showed that the optimal utilisation of the terraces corresponded to the demographic optimum in the mid-19th century. After the Second World War, there was a gradual abandonment of the terraces, with significant differences between mountain regions. Nevertheless, the terraces remained intact despite these developments and survived the extreme event under investigation. This confirms the hypothesis of resilience and provides important insights for future strategies to revitalise these landscapes in the context of climate change

In the study by Garzón-Oechsle et al. [138], a mobile LiDAR-based mapping system (MMS) without the use of UAVs was used to map the terrain around the documented stone architecture of the Manteños (ca. 650-1700 AD). The study area covered 1.2 km² in the cloud forests of Bola de Oro, Manabí, Ecuador. The resulting digital terrain models (DTMs), when combined with soil surveys and archaeological excavations, revealed a Manteño landscape that had been significantly altered by the construction of agricultural terraces, drainage channels, and water retention basins. These structures were designed to store and distribute water from seasonal rainfall and marine layers at higher altitudes. The extensive investment in this sophisticated landscape is likely due to the fact that the Chongón-Colonche Mountains were considered resilient areas to extreme climate changes associated with the El Niño-Southern Oscillation (ENSO) during the Medieval Climatic Anomaly (MCA, ca. 950-1250 AD) and the Little Ice Age (LIA, ca. 1400-1700 AD) [138].

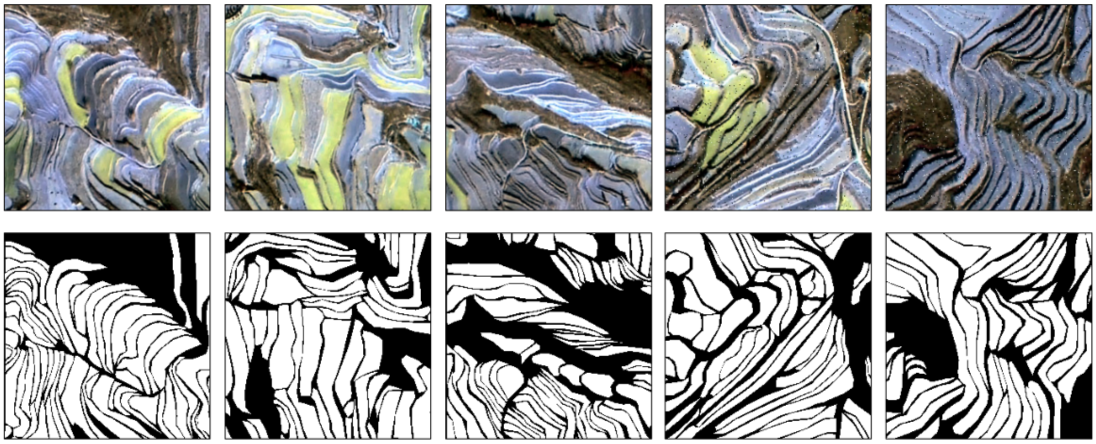

Figure 10. GF-2 RS Data of fused image and their corresponding labels for detection of terrace. The top row shows the GF-2 RS Dataset of fused images. The bottom row represents the true labels correponding to the GF-2 sample set of fused images (From Yu et al.[131]).

4.2.3. Genesis Indicators of A-LUI - Allmenden

Allmenden refers to communally used areas that played a central role in pre-modern agricultural societies. The term originates from the medieval legal system and referred to areas that were not privately owned by individuals, but were used jointly by several or all members of a village community. In Europe, commons were widespread and were an important addition to private farmland, particularly in the three-field economy. In England, Germany and other parts of Europe, numerous commons were privatised in the 17th-19th centuries, which often caused social tensions. Remnants of historical commons have been preserved, for example in alpine pastures, heathland or traditional co-operative forests

Modern RS methods can be used to effectively record historical field systems and commons. The combination of different technologies, including LiDAR (Light Detection and Ranging) as well as multispectral and hyperspectral satellite images, is particularly powerful. LiDAR has the advantage that it can penetrate vegetation and detect fine ground elevations and structures. This makes it

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possible to identify relics of earlier landforms, vaulted fields, hedge structures and medieval paths. A practical application example is the discovery of former three-field farming areas and commons that are now covered by woodland or modern agriculture. Medieval plough tracks and plot structures, particularly in Great Britain, Germany and France, can also be detected using this method. In addition, multispectral and hyperspectral satellite images make it possible to differentiate between different soil types and vegetation cover, allowing conclusions to be drawn about historical agricultural use. Deviating vegetation structures also help to identify historical field boundaries. Former agricultural areas often show characteristic vegetation patterns or soil features that can be visualised using these techniques. Hyperspectral analyses also offer the possibility of identifying differences in moisture content, soil chemistry or erosion patterns, which provides additional insights into past land use practices.

Edisa Lozić [139] analysed the use of airborne LiDAR data to discover, document and interpret agricultural land use systems in the early medieval microregion of Bled (Slovenia). By combining LiDAR data with archaeological, geological and pedological analyses, significant environmental variations within a microregion were identified. These enabled a detailed reconstruction of early medieval settlements and their agricultural use. The study by Masini et al. [140] investigated the effectiveness of LiDAR data for reconstructing the urban form of a medieval village near Matera, southern Italy. The research shows how LiDAR data can be used to reconstruct the urban structure and architectural features of historical settlements, even in densely forested or difficult to access areas.

4.2.4. Genesis Indicators of A-LUI - Deforestation

The recording of deforestation to gain pasture or arable land is an essential indicator of land use intensity (LUI). It allows a detailed analysis of human interventions in the environment, especially with regard to changes in the carbon balance, biodiversity loss, resource utilisation and soil changes. Modern RS technologies offer precise methods for measuring these environmental changes and assessing their ecological consequences over longer periods of time. Global deforestation shows significant losses of forest area in different regions of the world. The study "Forest Pulse: The Latest on the World's Forests" describes the latest trends in forest loss and deforestation and provides an up-to-date assessment of the global state of forests (https://gfr.wri.org/latest-analysis-deforestation-trends). According to Smith et al. [141], the global forest cover was around 4.06 billion hectares, with approximately 420 million hectares lost between 1990 and 2020, mainly in tropical regions.

Slash-and-burn agriculture plays a significant role in the deforestation process and causes serious climate effects, including temperature increases, changes in precipitation patterns and loss of biodiversity [142]. The use of unmanned aerial vehicles (UAVs) to analyse land cover during slash-and-burn has shown that multispectral imagery enables rapid and accurate assessment of land use change. In the future, this technology could serve as a standard method for recording slash-and-burn events [143]. The use of satellite imagery has proven to be one of the most efficient methods for the comprehensive and regular recording of deforestation. Optical satellites such as Landsat or MODIS provide high-resolution images that can be used to detect forest loss [144]. However, they are limited by weather conditions and cloud cover. RADAR systems such as Sentinel-1, on the other hand, work independently of light conditions and atmospheric influences, which makes them a reliable alternative for forest monitoring [145,146] . In addition, high-resolution satellite images make it possible to identify smaller deforested areas that are often overlooked in large-scale analyses [147]. The combination of different RS technologies can thus provide a comprehensive analysis of global deforestation and contribute to the development of effective conservation measures (see Figure 11).

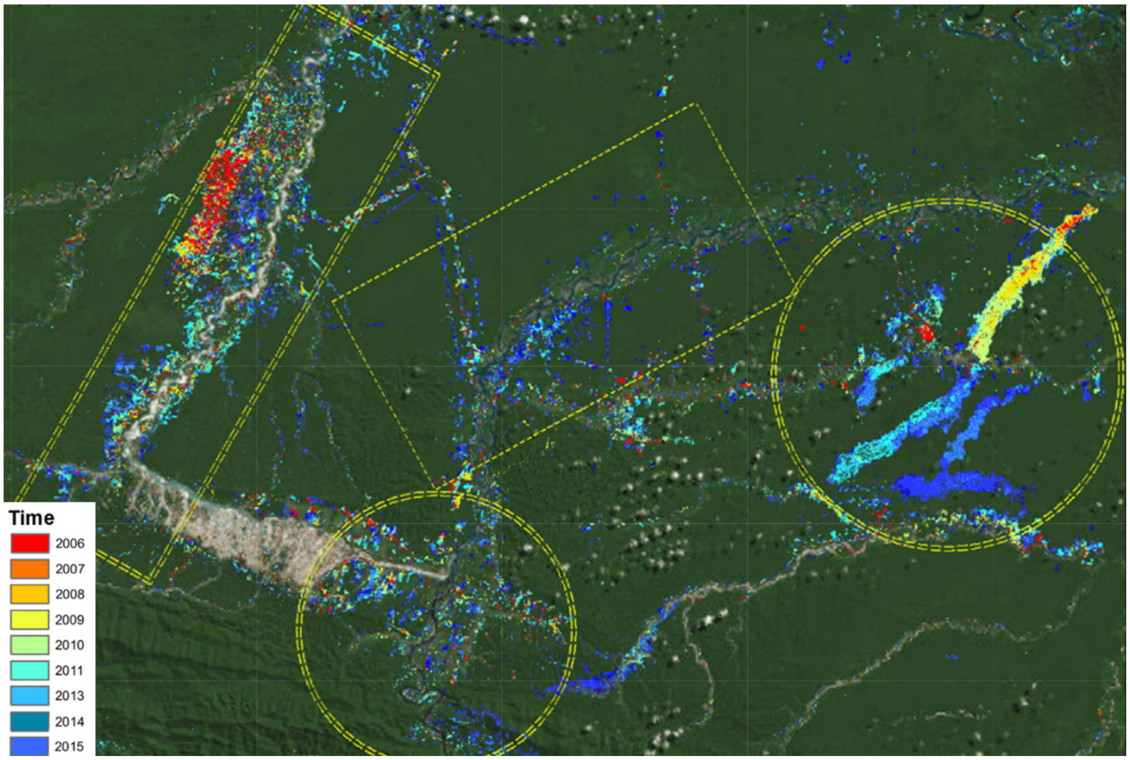

Figure 11. The deforestation events detected from the time series of photosynthetic vegetation in the Peruvian site. Deforestation is for the period from 2006 to 2016 and it was detected using the mean and standard deviation of RS time series data (Landsat 1990-2016) (from Tarazona et al. [147]).

4.3. Monitoring the Structural Indicators of A-LUI with RS

"The structural indicators of LUI, namely, the diversity of the composition and configuration of LUI characteristics" (modified after Lausch et al. [62] (see chapter 4). Table 3A contains numerous examples, sensors and references.

4.3.1. Structural A-LUI Indicators - Crop Composition and Configuration

The quantification of landscape structure and the derivation of structural indicators play a decisive role in the monitoring of land use intensity (LUI). For example, the extraction of farmland boundary from RS data is a key LUI indicator and supports agricultural planning, resource conservation and sustainable development. Field boundaries are defined by changes in the type of crops planted, which are visible in RS data as discontinuities in grey value, colour or texture. Wang et al. [148] provides a comprehensive overview of Farmland Boundary Extraction using RS data. Spatially high-resolution satellite images (≤1 m) such as WorldView-2/-3 (0.3-0.5 m), QuickBird (0.61 m), Pleiades (0.5 m) or GeoEye-1 (0.41 m) are particularly suitable for capturing field boundaries, as they allow fine structures such as narrow field paths and small plots to be captured. Medium-resolution satellite data (1-5 m) such as Sentinel-2 (10 m, with super-resolution at 5 m), Landsat 8 & 9 (30 m, for large-scale land use analyses), GF-2 (1 m, Chinese satellite) or RapidEye (5 m, multispectral available) are also suitable for large-scale analyses [148] see Figure 12.

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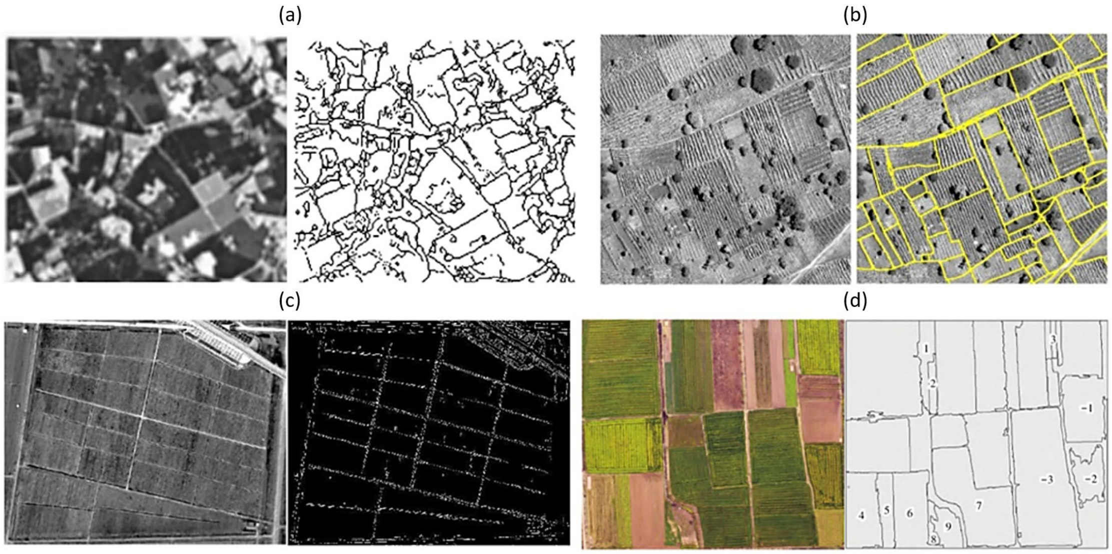

Figure 12. Different forms of farmland boundaries in RS imagery: (a) threads in farmland imagery, (b) demarcation lines between farmlands, (c) boundary objects between farmlands, (d) perimeter boundaries of farmland blocks, (d) is the the number of the farmland forms of farmland boundaries monitored by RS (from Wang et al. [148]).

Table 149. RS Data enable the quantification of field sizes and their spatial distributions, which allow conclusions to be drawn about the degree of LUI and its management practices. Large, contiguous areas on which a single plant species is cultivated are indicative of industrial agricultural practices [150]. The arrangement of such monocultures can be easily recognised by RS and is a structural characteristic of intensive use. High-resolution satellites (Sentinel 2, Word View, Rapid Eye) show these agri. Areas appear as numerous small, geometric fields that are often separated by paths or hedges. Here, the degree of LUI is shown by small, highly parcelled fields, which gives an indication of the maximum utilisation of the available land [67]Kümmerle et al. [31] use the image texture of Landsat data to derive the patch size, whereby the texture explained up to 93 % of the variability of the field sizes in the study area in the border region between Poland, Slovakia and Ukraine. The patch size (field size) indicator also offers the unique opportunity to investigate changes in land use that have occurred in post-socialist land reform strategies, as many large agricultural areas have been parcelled out through privatisation. For example, Figure 13 shows a Landsat RS dataset in the 1990s, which clearly shows the state border between Saxony-Anhalt and Lower Saxony north of the Harz Mountains due to the change in patch size and small-scale parcelling.

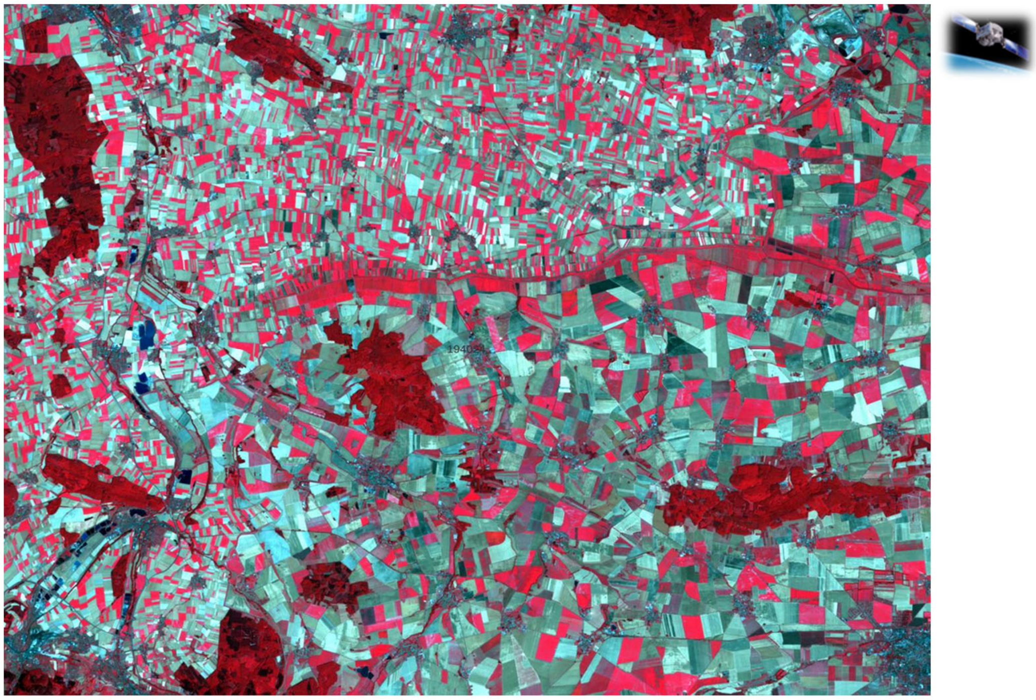

Figure 13. State border between the former FRG and GDR (different farming practices) after the fall of the Wall is clearly visible due to the shape, size and small-scale nature of the border between Saxony-Anhalt and Lower Saxony north of the Harz Mountains in the 1990s, Germany.

In the study by Roilo et al. [67] , various LUI indicators (e.g. field size, LULC_homogeneity) are used to analyse their effects on biodiversity. To calculate the field size, they used the LULC classification (2020, at 20 × 20 m resolution) [151], which was subsequently converted into polygons. The problem here is that not all crops could be properly classified using Sentinel 2 RS data. Furthermore, no roads and field paths could be included in the classification, which meant that the actual field size and the agricultural pattern could only be insufficiently quantified. In the study by Martin et al. [84] , which deals with the effects of farmland heterogeneity on biodiversity, field size is emphasised as an important indicator. In order to improve the accuracy of the derivation of field size, it is often derived vectorially from aerial image data[82] . In this study, Mohr et al. [83] used aerial image data in combination with in-situ data and interviews to answer the question Why has farming in Europe changed since the 1960s? In the study by Baessler and Klotz [152], historical and temporal time series of aerial image data were used to analyse changes in agricultural land-use on landscape structure and arable weed vegetation over the last 50 years. The Interspersion and Juxtaposition Index (IJI) quantifies the mixing of different land use types and reflects the heterogeneity of the landscape. Higher IJI values indicate a more complex, diversified landscape, which has potentially positive effects on biodiversity [153].

The Shape Index is also used to analyse differences in land use patterns and management practices between different regions, such as East and West Germany. Such analyses can provide information on the impact of different management practices on landscape structure and function [154]. Furthermore, shape indicators can be used, for example, to estimate operational efficiency, to justify the merging of two field plots or to facilitate land consolidation projects [155]. In his study, Oksanen [155] uses various shape indicators such as convexity, compactness, triangularity, rectangularity, ellipticity, the ratio of principal moments, the radius of the inscribed circle and the kerb index to classify the real field plots in order to quantify the operational efficiency (time and distance of the necessary travelling distance). Griffel et al. [156] examines the relationship between field shape and size and empirically derived crop efficiency to support assumptions related to the

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prediction of crop costs, greenhouse gas emissions, labour requirements and other factors that affect the willingness to grow energy crops. Salas and Subburayalu [157] used Airborne Hyperspectral AVIRIS and HYDICE datasets to assess the potential of an optimised shape index to discriminate between tillage types (maize-min and maize-notill) and between grass/pasture and grass/trees, tree and grass.

The indicator homogeneity of agricultural areas is a very good indicator for quantifying the LUI. Areas with high LUI are characterised by high homogeneity in species distribution and homogeneous spectral characteristics in contrast to organically cultivated areas with increased diversity of species (no use of pesticides) [158] . Blüthgen et al. [158] were able to prove through in-situ measurements at 150 grassland sites in the Biodiversity Exploratories in three regions in Germany (Alb, Hainich, Schorfheide) that the vascular plant diversity in grassland sites in two regions (Alb and Hainich) decreased significantly with the LUI. Important work on the assessment of homogeneity from RS data of landscapes can be found in Rocchini et al. [159] , which provides an overview of the current state of RS-based techniques for deriving spectral heterogeneity as a proxy of species diversity. Based on his approaches, Rocchini et al. [160] developed the Rao's Q diversity index, which is considered a remotely sensed spatial heterogeneity indicator for taxonomic and functional plant species diversity [161].

4.3.2. Structural A-LUI Indicators - Surface Roughness of the Vegetation

Closely related to homogeneity is the surface roughness of the vegetation, which describes the structural variability of the vegetation surface and provides valuable information on plant architecture, stand density, species distribution, cultivation methods and thus LUI. Intensively managed fields with monocultural cultivation generally have a low roughness (homogeneous stands), while more extensive, more diverse forms of cultivation or agroforestry systems have a higher roughness. Steele-Dunne et al. [162] provides an overview of RADAR RS of Agricultural Canopies (see Figure 14). RADAR RS technologies can be used for a variety of applications resulting from the detection of the surface roughness of vegetation in agricultural areas. These range from crop classification, vegetation dynamics, vegetation phenology, water stress and soil moisture derivation. Much of our understanding of vegetation backscatter from agricultural vegetation plots comes from SAR field-scale classification and monitoring studies [162]. Howison et al [163] used Sentinel-1 RADAR data to quantify the spatial dynamics of surface roughness of vegetation in agricultural landscapes. Herrero-Huerta et al. [164] use the roughness of plant features (soya beans) using UAV aerial image data to estimate biomass in agricultural systems. Alfieri et al. [165] use the roughness, canopy structure and configuration of vineyards to estimate the evapotranspiration loss required for irrigation and effective utilisation of limited water resources.

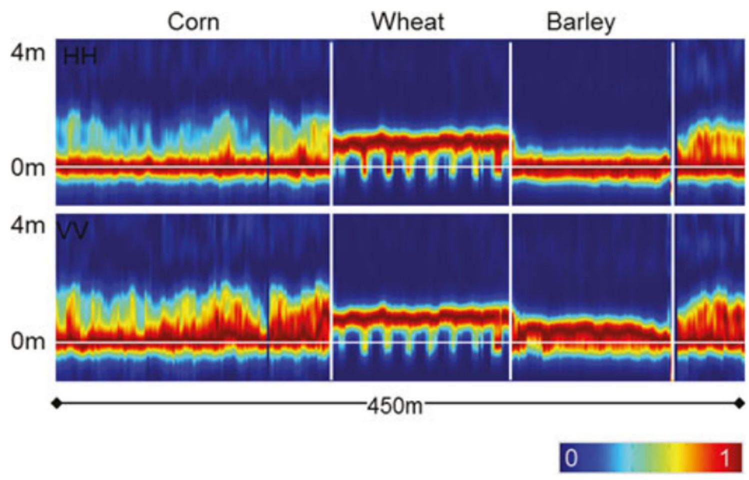

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Figure 14. Normalised termographic reflectivity profile across three fields (corn, wheat and barley) based on RADAR RS data (from Steele-Dunne et al. [162]).

4.3.3. Structural A-LUI Indicators - Soil Roughness

Soil roughness is a crucial indicator for LUI as it allows direct conclusions on tillage practices, water balance, erosion processes and vegetation development. Soil roughness is an inhomogeneous medium consisting of different types of soil textures, different shapes and sizes of stones, clods, SM gradients, organic matter, etc. The microwave signal incident on this layer is modified, scattered and attenuated due to the physical and structural properties of this medium [166]. Soil roughness thus reflects various physical and agronomic processes. For example, the intensity of soil cultivation (e.g. ploughing, harrowing) changes the soil roughness considerably. High roughness often indicates intensive mechanical interventions, while low roughness indicates minimal soil turnover or conservation agriculture (see Figure 15, 16). Different crops and management practices produce specific roughness patterns. During a vegetation cycle, a gradual smoothing of the soil can be observed due to natural processes (rain, wind, biological activity) or renewed roughness formation due to agricultural interventions. Furthermore, high soil roughness favours water infiltration, as depressions can store water. Too little roughness, on the other hand, favours surface runoff and increases the risk of erosion. Heavily tilled and therefore less rough soils are more susceptible to erosion, especially in dry areas. Roughness can therefore be used as an indicator for the risk of erosion and the sustainability of cultivation. Soil roughness influences the temperature and moisture distribution on the surface. High roughness can reduce soil warming and influence evaporation rates. By monitoring roughness, conclusions can be drawn about plant growth. Heavily cultivated soils with low roughness could, for example, indicate a high use of fertilisers and irrigation. It can be analysed very well using RS methods such as RADAR and LiDAR technologies as well as optical sensors [167].

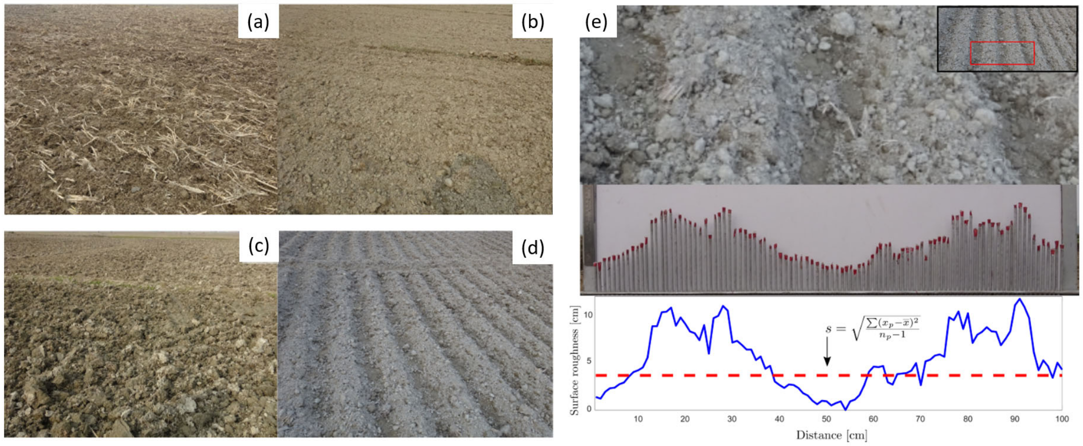

Figure 15. Field photographs to illustrate the surface roughness conditions in different agricultureal platz on the Kosi Fan. (a) shows the photograph of a stubble field, (b) harrow field, (c) ploughed field, (d) furrow field, (e) surface undulation profile extracted processing the photographs captured for the pin-profile using a digital camera in the field (from Singh et al. [166]).

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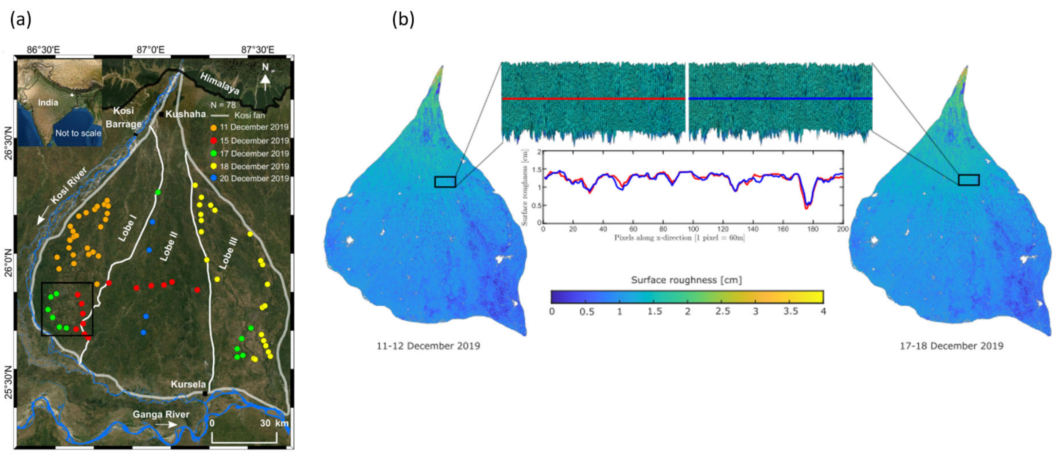

Figure 16. (a) Image in the top left shows the location of the Kosi megafan in the Himalayan Foreland, (b) spatial distributuion of surface roughness prediction from Sentinel-1, Sentinel-2 and Shuttle RADAR Topographic Mission (SRTM) data. (from Singh et al. [166]).

There are numerous other structural indicators that cannot be discussed further here. You will find numerous other examples of structural indicators that can be recorded using RS (see Table A3).

4.4. Monitoring the Taxonomic A-LUI Indicators with RS

"The taxonomic indicators of LUI, representing the diversity of LUI components that differ from a taxonomic perspective" (modified after Lausch et al. [62] (see chapter 4). Table 3A contains numerous examples, sensors and references.

4.4.1. Taxonomic A-LUI Indicators - Cropping Patterns

The monitoring of cropping patterns using RS is a key indicator of agricultural land use intensity (LUI). They enable precise characterisation of cropping intensity, harvest frequency, diversity and management strategies. With the help of RS such as multispectral, hyperspectral and RADAR data, changes can be analysed on a large scale and long-term trends in agriculture can be identified [150,168,169].

Extensive agriculture shows more variable patterns with longer fallow periods, especially in semi-arid or mountainous regions, and relies on crop rotation, mixed cropping or agroforestry. Single cropping indicates low intensity, while double/multi-cropping indicates high land use intensity (LUI), often under irrigated conditions in tropical and subtropical areas. Intercropping increases vegetation variability and is often used in sustainable agricultural systems. High LUI is associated with short or no fallow periods, while low LUI has longer fallow periods for soil regeneration. Long-term changes in cropping patterns can be indicators of soil degradation, water scarcity or climate change, which is why the adoption of diversification strategies such as agroforestry and mixed cropping as sustainable measures against overexploitation is essential. Mahlayeye et al. [168] gives a very good overview of the detection of cropping patterns using RS. Optical sensors are most commonly used for mapping single cropping, especially those with high spatial resolution, such as UAVs. These sensors enable precise identification of single crop fields, but are often only suitable for smaller areas. For large-scale (regional/global) analyses, on the other hand, medium to coarse resolutions are usually used, such as Spot, Landsat 8, MODIS or Sentinel-2 ,[170,171]. In addition to optical sensors, microwave sensors with high temporal resolution, such as RADARSAT-2 or Sentinel-1 [172], are also used, particularly for rice cultivation in Asia or maize in Africa. Some studies have combined microwave and optical sensors for more precise crop mapping [173]. In addition, hyperspectral or LIDAR sensors are increasingly being used [174–176]. Studies on the mapping of individual crops are based on phenology and the spatial distribution of crops. Mapping individual

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crops using single images may be insufficient, as plants change during the growing season. Continuous monitoring of plant development is therefore necessary. Overall, the analysis shows that single crop cultivation can be successfully mapped at both local and regional level with high spatial and temporal resolution [168]. The mapping of multiple cropping and sequential cropping systems is carried out at different levels using optical sensors with high temporal resolution [168]. MODIS satellite data are frequently used [177,178], while Indian RS (IRS) satellites and the Wide Field Sensor (WiFS) [179] and Sentinel 2[169] are also used in some studies. The detection of triple cropping patterns was also carried out [177]. Microwaves (Sentinel-1 C-band time series data) and optical sensors enable the creation of detailed temporal profiles of sequential crops [180,181]. Commonly mapped crops are maize, rice, wheat and soybeans, with studies on sequential cropping patterns increasingly being conducted in tropical regions characterised by long rainy seasons

Mapping sequential cropping patterns is more complex than single cropping, as different crops are planted in the same growing season, requiring a longer growing season and more continuous ground cover [168] . In particular, high-resolution multispectral and hyperspectral imaging provides valuable insights into the structure and dynamics of mixed crops. Vegetation indices such as the NDVI (Normalised Difference Vegetation Index) or the EVI (Enhanced Vegetation Index) help to differentiate between different plant species based on their spectral reflectance properties, while hyperspectral sensors enable even more precise differentiation by analysing specific wavelength ranges.

4.4.2. Taxonomic A-LUI Indicators - Crop Classifications

A study on high-resolution mapping of the German agricultural landscape using RS provides detailed insights into parcelling and field structures through crop classification. RS-based classifications of agricultural land use for the years 2017-2020 for the German agricultural landscape (grid of 10m x 10m) provide detailed insights into area size, distribution and crop type cultivated (https://ows.geo.hu-berlin.de/webviewer/landwirtschaft/index.html[182] see Figure 17). Crop types such as rapeseed or sugar beet can be differentiated very well. However, species that are spectrally very similar in the course of the growth phases or in their appearance (e.g. winter wheat and triticale) or that differ solely in terms of their type of utilisation (e.g. silage maize and grain maize) cannot yet be recorded with sufficient accuracy using RS. Patterns of land use intensity, such as crop rotation or fallow periods, can be effectively captured by time-series RS data, providing insights into the sustainability of agricultural practices. Preidl et al. [151] uses Sentinel-2A imagery data for crop classification on the national scale (Germany).

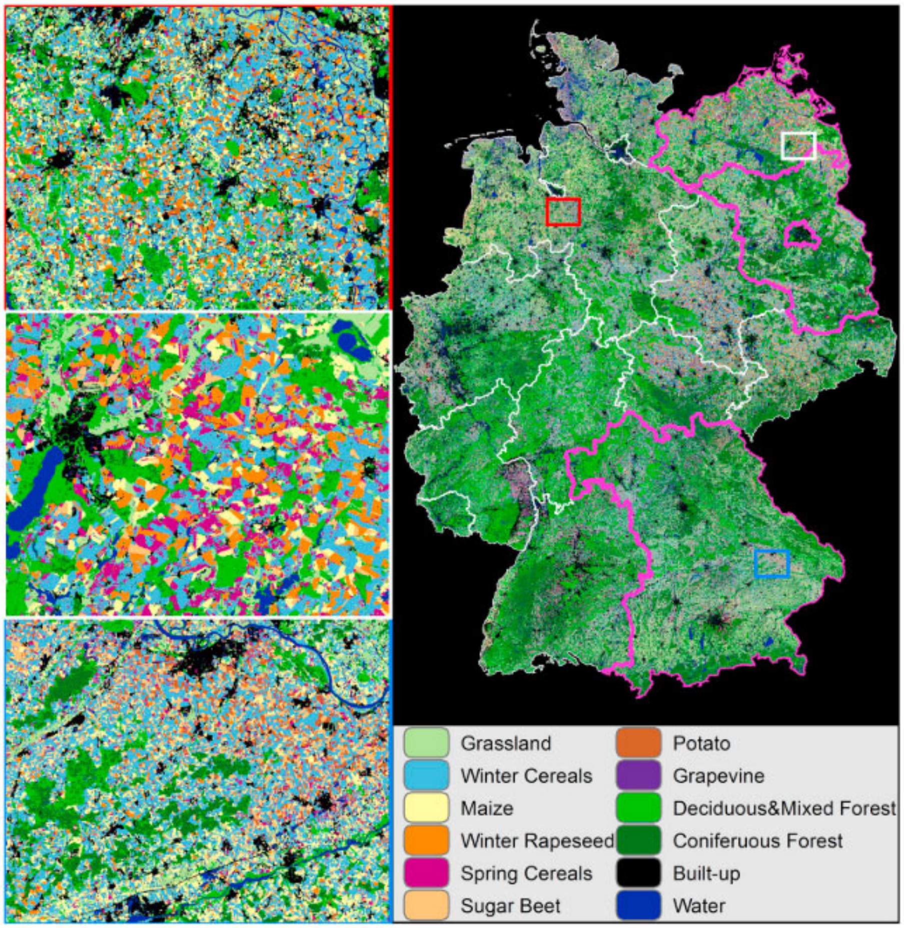

Figure 17. Results of the wall-to-wall crop type mapping using the bendchmark 10-day interval composite of Landsat and Sentinel-2 time series for Germany (from Griffiths et al. [182]).

The global distribution of LUI is crucial for understanding agricultural land use. Previous studies used coarse-resolution data, which are unsuitable for heterogeneous landscapes. To fill this gap, Zhang et al. [183] developed the global, spatially continuous CI dataset GCI30 with 30 m resolution using Landsat 7 ETM+, Landsat 8 OLI, and Sentinel-2 MSI time series during 2016-2018. GCI30 captures global patterns and spatial details, with monocultures dominating 81.57 % of cropland. Regional differences reflect natural and anthropogenic influences[183] . Howison et al. [163] developed a new RADAR-based RS technique for large-scale quantification of A-LUI. The method utilises the temporal stability of RADAR signals to capture differences in land use and provides more precise tracking of LUI at the landscape scale.

4.4.3. Taxonomic A-LUI Indicators - Intensification of Grassland

The intensification of grassland utilisation (e.g. more frequent mowing, increased grazing) significantly impairs biodiversity and ecosystem services. However, detailed information on utilisation intensity is usually locally limited. Numerous studies show [35,184] that mowing events can be mapped over large areas using satellite image time series. Time series phenology can overcome limitations of classification-based mapping approaches, especially when characterising grassland use intensity, using the frequency and timing of mowing events as important indicators [185]. Lange et al. [184] developed a method for the RS-based derivation of grassland intensity for Germany (www.ufz.de/land-use-intensity). Based on Sentinel-2 time series (spatial resolution of 20m) from 2017 and 2018, the NDVI time series data and available in-situ indicators (grazing intensity, mowing frequency and fertiliser use) of the Biodiversity Exploratories for Germany [186] were used to train

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and derive a continuous LUI index for grassland for Germany using Convolutional Neural Networks (CNN). An overall classification accuracy of up to 66 % for grazing intensity, 68 % for mowing and 85 % for fertilisation was achieved. Weber et al. [35] developed a rule-based algorithm for mapping mowing and grazing events in Switzerland (2018-2021) based on Sentinel-2 and Landsat-8 data. The validation was carried out with time series data from public webcams. The review (2020-2021) showed that ≥78 % of the recorded events reflect actual management, but up to 57 % - especially grazing events at higher altitudes - were not recognised. Bartold et al, [187] presents a comprehensive study on the classification of management intensity of grasslands in two different regions of Poland (see Figure 18). By using Sentinel-1 and Sentinel-2 data synergistically, different intensity types could be identified, allowing conclusions to be drawn about herbicide use.

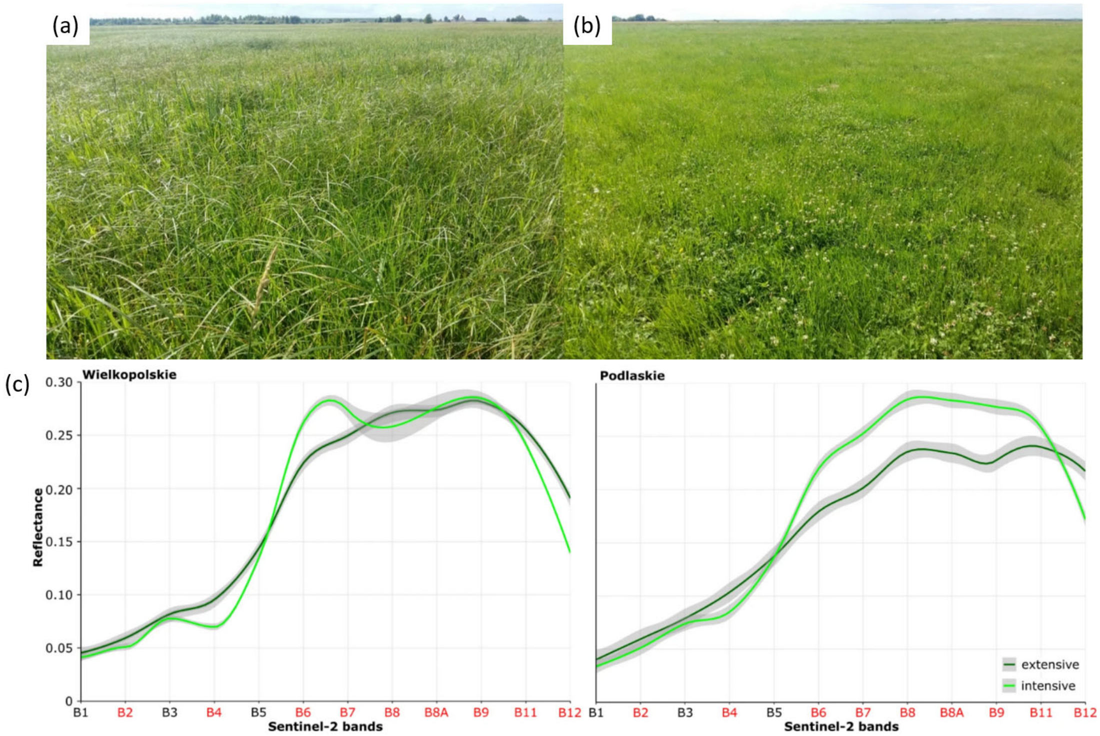

Figure 18. Types of grassland management intensity at the Podlaskie study sites, (a) extensive, (b) intensive, (c) comparison of spectral curves for intensive and extensive grasslands averaged with the loess algorithm (span = 0.35, confidence interval = 0.95) based on Sentinel-2, (from Bartold et al. [187]).

There are numerous other taxonomic indicators that cannot be discussed further here. You will find numerous other examples of taxonomic indicators that can be recorded using RS in the Table A3.

4.5. Monitoring the Functional A-LUI Indicators with RS

"The functional LUI indicators, which is the diversity of LUI functions and processes, as well as their intra- and interspecific interactions" (modified after Lausch et al. [62] (see chapter 4). Table 3A contains numerous examples, sensors and references.

4.5.1. Functional A-LUI Indicators - Plant Density and Biomass Production

RS for recording plant density and biomass production is essential for analysing vegetation structures and assessing the LUI, as it reflects the direct effects of management practices on vegetation. RS technologies enable the area-wide analysis of vegetation parameters using the

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Normalised Difference Vegetation Index (NDVI), the Soil-Adjusted Vegetation Index (SAVI) and the Enhanced Vegetation Index (EVI) to minimise soil and atmospheric influences in order to determine plant density and biomass production. Recent studies, for example by Sousa Júnior et al. [188], demonstrate the successful use of Landsat 8 to estimate above-ground biomass in agricultural mosaics. The combination of different sensor systems, especially optical and RADAR-based RS technologies, improves the accuracy of biomass estimates [189]. The use of unmanned aerial vehicles (UAVs) offers an efficient alternative due to high spatial resolution and flexibility [190,191]. Da et al. [191] combined UAV-derived spectral, textural and structural features for biomass monitoring of soybean and achieved a model accuracy of $R^2 = 0.85$. Spaceborne RS data are also used to assess plant biomass. Breunig et al. [192] used PlanetScope and Sentinel-1 SAR data to monitor intercrop biomass in southern Brazil. Hagn et al. [193] analysed Sentinel-2 data to model crop-specific biomass yield potential in precision farming. Their results showed a strong correlation between relative biomass potential (r = 0.62-0.73) and soil properties such as soil organic carbon (SOC) and total nitrogen (TN). However, optical satellite systems such as Landsat and Sentinel-2 are weather-dependent and do not collect data under cloudy conditions. To overcome this limitation, Planet developed the Biomass Proxy product [194] , which provides a daily, ready-to-analyse biomass estimate with 10 m spatial resolution. The Biomass Proxy algorithm fuses Sentinel-1 and Sentinel-2 data and enables continuous monitoring of vegetation. This facilitates the early detection of growth anomalies, the assessment of crop yields and the identification of potential environmental hazards and supports informed agronomic decision-making. Difference map of Abovground Biomass (AGB) estimaates of 18. August 2017 and 26. August 2017 derived from PlanetScope (PS) optical, Sentinel-1 Synthetic Aperture RADAR (SAR), and hybrid (optical plus SAR) datasets (see Figure 19).

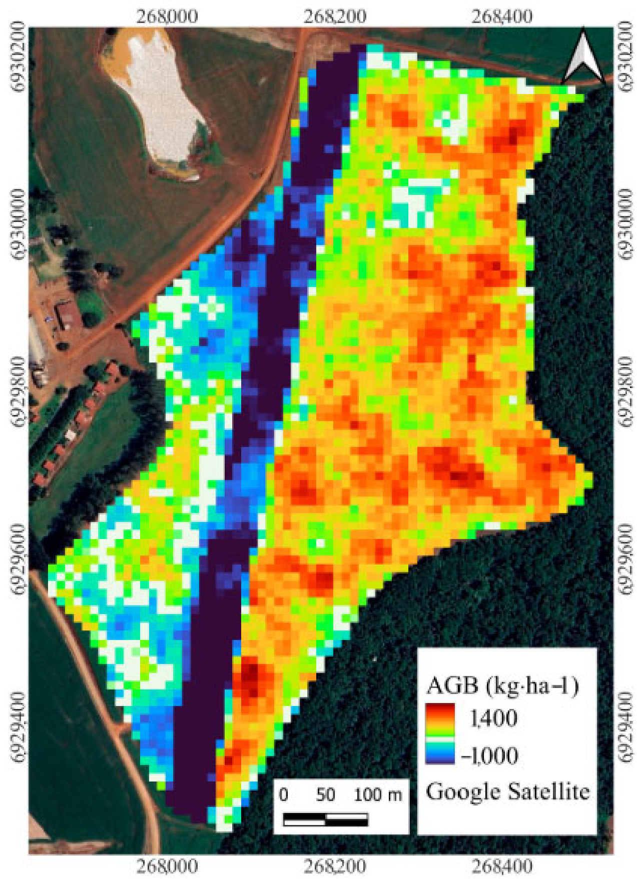

Figure 19. Difference map of Abovground Biomass (AGB) estimaates of 18. August 2017 and 26. August 2017 derived from PlanetScope (PS) optical, Sentinel-1 Synthetic Aperture RADAR (SAR), and hybrid (optical plus

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SAR) datasets. Reddish tones indicate AG increase and blue tones indicate AGB decrease. White areas indicate low AGB variation (from Breunig et al. [192]).

4.5.2. Functional A-LUI Indicators – Pesticide, Herbicide and Fungicide

The use of pesticides and herbicides is an important indicator for assessing the LUI. The use of pesticides and herbicides causes vegetation-related changes and stress reactions in plant populations, which can be recorded using RS via vegetation anomalies. Herbicides specifically influence metabolic processes by disrupting biochemical reactions, e.g. triazines (atrazine) lead to the inhibition of photosynthesis, glyphosate to the blocking of amino acid synthesis or auxin analogues (2,4-D) to the impairment of cell growth. These effects can be detected in the short term by spectral analyses of RS data

The RS-based recording of pesticide intensity is a growing field of research with the aim of making crop protection more efficient and environmentally friendly, as well as being able to detect the use of pesticides and herbicides. The use of satellite images, drones and hyperspectral sensors allows conclusions to be drawn about the use and distribution of pesticides. While current applications are primarily focussed on laboratory analyses with hyperspectral sensors (e.g. ASD, MSV-500) [195–199], space-based RS data such as Sentinel-2 are also being used [200]. Spectral reflectance data, particularly in the red and near infrared range, enable the calculation of vegetation indices such as NDVI, whose changes indicate herbicide applications and associated stress reactions [200] . Hyperspectral RS captures detailed spectral signatures that can identify specific pesticide applications and their effects [196] . For example, hyperspectral imaging combined with machine learning has been used to detect herbicide stress early and identify new sites of action. Zhang et al. [197] extracted the Physiological Reflectance Index (PRI) and NDVI from hyperspectral images and classified glyphosate-induced plant damage using Support Vector Machine (SVM). Chu et al. [198] used neural networks to identify different herbicide damage to wheat, finding significant spectral differences in the wavelength ranges 518-531 nm, 637-675 nm and at the red edge. Pon Arasan et al. [201] analysed UAV-based mapping methods to optimise herbicide use. Bartold et al.[187] combined Sentinel-1 and Sentinel-2 data to classify management intensities in Polish grasslands and identified herbicide applications. Bautista et al. [187] investigated the efficiency of drone applications with cyhalofop-butyl in Spanish rice fields using NDVI analyses with Sentinel-2. Sentinel-2 and Landsat-8/9 are suitable for general monitoring, while PRISMA and EnMAP enable more precise spectral analyses. WorldView-3 offers high spatial resolution for detailed field studies. The combination of these satellites allows monitoring of pesticide and herbicide use. Exemplary application of SugarViT (Vision Transformer based model for disease severity) for disease severity prediction in sugar beet using UAV multispectral data. Each prediction is completely independent of its surrounding predictions [202] (see Figure 20).

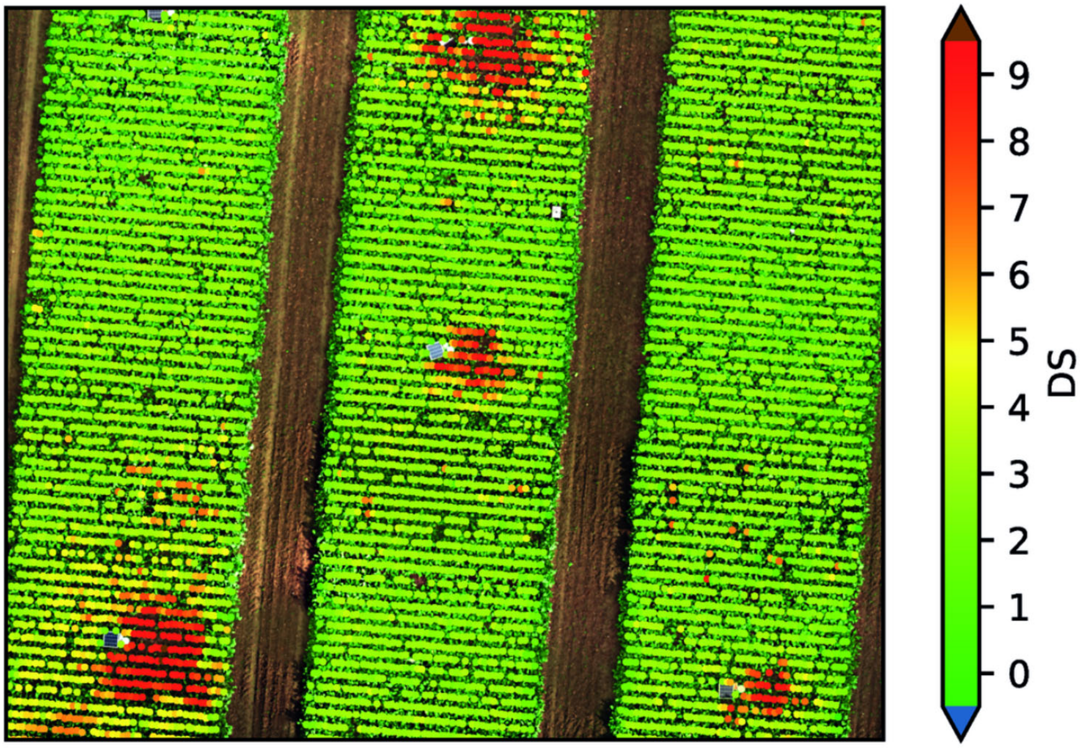

Figure 20. Exemplary application of SugarViT (Vision Transformer based model for disease severity) for disease severity prediction in sugar beet using UAV multispectral data. Each prediction is completely independent of its surrounding predictions. The model shows a highly consistent prediction behavior (from Günder et al. [202]).

4.5.3. Functional A-LUI Indicators - Fertilisation Intensity

Recording fertilisation intensity using RS (RS) is central to precision farming and allows conclusions to be drawn about LUI. For example, the intensive use of fertilisers and pesticides promotes a homogeneous and vital vegetation pattern by increasing plant growth and yield quality. Precise nutrient monitoring includes plant traits and nutrient information, with imaging spectroscopy as a key method to determine the nutrient status of crops and soil availability quickly and non-destructively. However, there are challenges as macro- and micronutrients, stress factors and phenological development stages have similar spectral signatures, which favours confusion at different scales.

Vegetation indices such as the Normalised Difference Vegetation Index (NDVI) quantify plant health and density and provide information on fertilisation and management practices. NDVI is often used to measure plant vigour and derive fertiliser recommendations. Li et al. [203] demonstrated UAV-based hyperspectral imaging to optimise nitrogen stress indices in maize. The Normalised Difference Red Edge Index (NDRE) more precisely determines the chlorophyll and nitrogen content of plants, which Li et al. [203] confirmed for maize. The chlorophyll index also serves as an indicator for the nutrient status, whereby hyperspectral data enable an exact determination of the chlorophyll content[203] . Yin et al. [204] used ensemble learning models and Sentinel-2 data to quantify the nitrogen concentration and above-ground biomass of potato plants with a coefficient of determination R^2 of 0.74. Almawazreh et al. [205] used UAV to investigate the effects of nitrogen fertilisation on the canopy temperature of agricultural crops in southern India. Increased nitrogen applications reduced the leaf temperature of maize by 2.1 °C and finger millet by 1.3 °C under sunny conditions. Hossen et al. [206] developed an AI-based, near real-time multispectral sensor solution for drones to accurately estimate the nitrogen content in the soil.

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4.5.4. Functional A-LUI indicators - Soil Organic Carbon (SOC)

Soil organic carbon (SOC) is a key component of soil quality and plays a crucial role in the global carbon cycle[207] . Higher LUI (e.g. heavy fertilisation, frequent tillage) generally leads to a decrease in soil organic carbon, as ploughing, erosion and humus decomposition mineralise carbon more quickly and release it as CO_2. Furthermore, LUI influences plant cover and biomass production, which in turn has an impact on carbon storage in the soil. Precise mapping and monitoring of SOC is necessary to develop sustainable agricultural practices and optimise carbon storage in soils.

RS enables efficient and cost-effective monitoring of large areas, provides data from regions that are difficult to access and allows the continuous recording of SOC dynamics with high temporal resolution [208] . Research on satellite-based SOC mapping started in the 1990s with Landsat TM data, where first correlations between spectral signatures and SOC concentrations were found [209]. These early studies showed promising results, but the spatial resolution was limited to 30 m and correlations often only reached R^2 values around 0.5, indicating high uncertainties [210]. In the 2000s, high-resolution RS data was combined with ground-based measurements to better map the spatial variability of SOC. Initial attempts to couple soil chemical properties with the Normalised Difference Vegetation Index (NDVI) method from Landsat data demonstrated the importance of vegetation cover for SOC modelling [211] . Studies show that multispectral, hyperspectral and RADAR sensors on satellite platforms can provide crucial data for SOC mapping [212]. However, optical RS is subject to certain limitations, particularly due to cloud cover. One possible solution is to combine optical and RADAR-based data [213]. With the introduction of the Sentinel-1 and Sentinel-2 satellites in the 2010s, SOC mapping improved significantly. Sentinel-2 provides multispectral images with a resolution of up to 10 metres, while Sentinel-1 provides RADAR images that can be used regardless of weather conditions [213,214]. RADAR data, in particular Synthetic Aperture RADAR (SAR), has potential for SOC mapping [212,215,216], but parameters such as polarisation, band frequency, orbit and time window significantly influence the accuracy of the models [217,218]. For example, SAR signals interact differently with vegetation layers depending on wavelength, which means that C-band and L-band systems differ in their applicability. Nevertheless, comprehensive analyses comparing different optical and RADAR-based sentinel satellites (Sentinel-1/2/3) for SOC mapping are still rare. In recent years, deep learning algorithms and hybrid models have proven to be particularly promising. Recent studies combine optical (Sentinel-2) and RADAR-based (Sentinel-1) RS data to further improve accuracy [219]. In addition, AI-based methods such as Random Forest, Light Gradient Boosting Machine (LGBM) and neural networks have been successfully used for SOC mapping [220,221]. Mean SOC content and C:N ratio maps predicted by 100 runs of BRT in Model V at a resolution of 100 m and their corresponding standard deviation maps (Model V: all available predictors, Sentinel 1-predictors, Sentinel-2 predictors, Landsat-8 predictors, Climate-predictors, Topography-predictors) [222] (see Figure 21).

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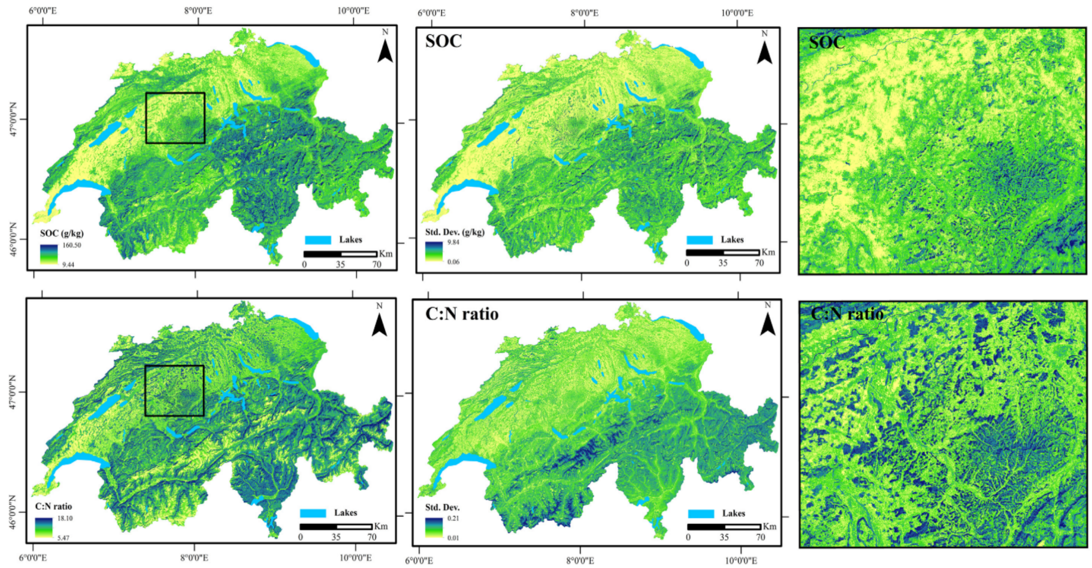

Figure 21. Mean SOC content and C:N ratio maps predicted by 100 runs of BRT in Model V at a resolution of 100 m and their corresponding standard deviation maps (Model V: all available predictors, Sentinel 1-predictors, Sentinel-2 predictors, Landsat-8 predictors, Climate-predictors, Topography-predictors) (from Zhou et al. [222]).

There are a large number of other functional LUI indicators, which could only be discussed selectively here. An overview of functional LUI indicators that can be recorded using RS can be found in Figure A1. Numerous others can be found in the Table A3.

5. New Approaches for the Quantification and Evaluation of A-LUI Using RS

5.1. RS and AI for Recording A-LUI

The precise recording of LUI is central to quantifying the impact of agricultural management on ecosystems and developing sustainable strategies. Recently, RS and artificial intelligence (AI) have established themselves as key technologies for recording agricultural utilisation intensities on a large scale, promptly and objectively [223]. RS data and its time series such as Sentinel-2, Landsat-8, MODIS or WorldView-3 provide high-resolution information on vegetation, soil surface and hydrology, allowing numerous indicators to be derived (see Table A3), which are closely related to agronomic interventions such as fertilisation, tillage, detection of crop rotations, harvest cycles and tillage patterns or multiple harvests per year as characteristics of LUI [224,225].

A critical step in interpreting this data is the integration of AI methods, in particular machine learning and deep learning, which can recognise complex, non-linear patterns in large, heterogeneous data sets. AI models such as Convolutional Neural Networks (CNNs), Support Vector Machines (SVMs) or Random Forests (RF) have been successfully used many times in the literature to quantify characteristics such as nutrient availability, plant health or management practices [225–227]. For example, Castaldi et al. [228] used Sentinel-2 data to derive soil organic carbon, indicating many years of intensive use. Shi et al. [229] combined RGB images with Backpropagation Neural Networks (BPNN) to estimate nitrogen accumulation and biomass in rice fields. This allows conclusions to be drawn about fertiliser intensity and growth potential. Sahabiev et al. [230] extended these approaches by incorporating soil characteristics (e.g. organic carbon, soil texture) into ML models for the spatial prediction of nutrient distributions. A particularly relevant example in the context of utilisation intensity is the use of CNNs to detect crop cycles, which is made possible by time series of satellite images (e.g. Sentinel-2 or MODIS). The detection of multiple harvests or intensive crop rotations is possible by analysing NDVI time histories [231,232]. In this context, Wang et al. [225] demonstrated that a combined LSTM-CNN model, trained with weather and soil data, was able to provide very precise predictions of the winter wheat harvest in China - a direct measure of output intensity.

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Various methods have also been established for nutrient intensity. Jaihuni et al. [233] used deep learning to estimate the spatio-temporal distribution of nitrogen, potassium and phosphorus.

Despite these successes, challenges remain: The technical complexity of RS data processing requires specialised expertise and high-performance infrastructures [223]. High-resolution data material, such as UAV-based hyperspectral images, is often only available locally. There is a lack of standardised definitions and indicators for deriving LUI, which makes comparability between regions difficult [234] . In addition, many deep learning models are difficult to interpret - a problem that recent work on Explainable AI (XAI) aims to counteract

Nevertheless, the future prospects are extremely promising. New architectures such as edge cloud computing or the edge cloud continuum make it possible to process large amounts of data in a decentralised manner on sensors and drones [223]. At the same time, methods such as transfer learning or few-shot learning allow models to be adapted for new regions with little training data [225,235]. This could make globally standardised, AI-supported maps of land use intensity a reality - a valuable tool for agricultural policy, climate protection and sustainable land use worldwide [223].

5.2. Semantic Web and Linked Open Data for the Monitoring of A-LUI

The assessment of A-LUI is a multidimensional and complex challenge that is at the centre of sustainable land management and environmental monitoring. It requires the integration and analysis of diverse data sources and data formats, including RS, soil, hydrology, vegetation and climate data as well as socio-economic information. The application of Semantic Data Integration (SDI) and Linked Open Data (LOD) opens up new possibilities for linking this heterogeneous data in a structured, interoperable and machine-readable way. This enables a comprehensive, consistent and scalable evaluation of the A-LUI [236,237]. Semantic technologies create the basis for context-aware data links and the development of cross-domain data models, making automated, knowledge-based analyses of agricultural systems feasible.

Ontologies, which represent domain-specific knowledge in formalised, standardised and machine-interpretable structures, play a central role in semantic integration. For the agricultural sector, AGROVOC - the controlled vocabulary of the Food and Agriculture Organisation of the United Nations (FAO) - is particularly well established (https://agrovoc.fao.org). The SWEET ontology (Semantic Web for Earth and Environmental Terminology, https://sweetontology.net) is relevant for environmental and climate data, which describes concepts such as vegetation cover, erosion risk and water availability - all of which have a direct influence on agricultural use. In addition, the INSPIRE initiative of the European Union (https://inspire.ec.europa.eu) offers standardised data models for geodata, which are essential for the integration of European land use information in particular.

In the area of soil data, the Global Soil Partnership (GSP), in collaboration with the FAO, is playing a leading role in the harmonisation and opening up of global soil data. The development of the Global Soil Information System (GloSIS) and the associated ontology (https://agroinformatics.org/glosis) represents a semantically sound model that integrates different soil data formats worldwide into a common framework. This enables a standardised assessment of soil fertility, susceptibility to erosion or nutrient availability in the context of actual agricultural use [238].

RS data is an integral part of the A-LUI assessment as it provides objective, comprehensive and temporally resolved information on biomass, vegetation dynamics and cultivation intensities. Semantic modelling is essential to exploit this potential and to link the data seamlessly with other sources of information. The SOSA/SSN ontology of the W3C (https://www.w3.org/TR/vocab-ssn/) enables the structured modelling of sensors, observations and platforms such as sentinel satellites, including their temporal-spatial properties. In combination with the SWEET ontology, complex geoscientific interrelationships - for example between climatic conditions, soil moisture and NDVI curves - can be consistently modelled. This is complemented by PROV-O for describing the origin of the data and GeoSPARQL for semantic modelling of geographical geometries and spatial relationships. Another important resource is the EO4GEO ontology from the EU project of the same name (https://www.eo4geo.eu), which was developed specifically for earth observation data, services and competences. It allows the semantic description of EO products such as satellite scenes, land cover maps or growth phase models and their integration with other domain-specific ontologies such as AGROVOC or GloSIS.

Current scientific work emphasises the practical benefits of semantic technologies: Hitzler et al. [239] show how semantic models significantly improve the integration and utilisation of geoscientific information. Further scientific studies demonstrate the practical applicability of semantic technologies for LUI assessment. Fibriani et al. [240] show the use of LOD to integrate heterogeneous spatial data sources for agricultural suitability analyses. Ranatunga et al. [241] addresses the challenges of integrating heterogeneous environmental geodata through a framework based on Ontology-Based Data Access (OBDA). It shows how semantic web technologies can improve the interoperability and integration of geodata. The study by Wang et al, [242] develops an ontology-based framework for the integration of RS imagery, image products and in-situ observations. The extension of the Semantic Sensor Network (SSN) ontology enables the comprehensive utilisation of heterogeneous observations. Potnis et al. [243] developed a RS Scene Ontology (RSSO) that derives spatial-topological and directional relationships between land use and land cover regions. This enables the creation of knowledge graphs for satellite scenes that can be enriched with domain-specific ontologies. Aldana-Martín et al. [244] present the RESEO ontology, which was developed for the semantic modelling of RS data and metadata in the field of earth observation. The ontology aims to standardise and integrate different types of RS data products and their metadata. Hamdani et al. [245] proposes a framework that enables semantic integration and advanced querying of raster data cubes based on the Virtual Knowledge Graph (VKG) paradigm. It defines a semantic representation model for raster data cubes that extends the GeoSPARQL ontology and allows the semantics of raster data to be combined with feature-based models, including geometries and spatial and topological relationships.

In addition to biophysical data, socio-economic information [246] is also essential for the LUI analysis. Data on farm sizes, market prices, subsidy instruments or tenancies provide context for agricultural decisions and utilisation patterns. They can be integrated into a coherent overall system using semantic models. The technical basis for this is RDF (Resource Description Framework), OWL (Web Ontology Language) and SPARQL as a query language. This makes it possible, for example, to specifically identify areas with intensive use and high environmental impact or declining yields.

Linking local and national data sources with global LOD services - such as FAOSTAT (https://www.fao.org/faostat/en/), Copernicus Land Monitoring (https://land.copernicus.eu), Open Land Use Map (https://hub.opensenselab.org/open-land-use/) and ISRIC World Soil Information (https://www.isric.org) - creates additional added value for cross-national comparative studies and monitoring approaches. A milestone for the practical implementation of these semantic concepts is the focus group "AI and IoT for Digital Agriculture" (FG-AI4A) initiated by the International Telecommunication Union (ITU) and the FAO. This group developed a reference architecture for digital agriculture (https://www.itu.int/en/ITU-T/focusgroups/ai4a/Pages/default.aspx) that integrates semantic data models, interoperability standards and AI-supported services. The architecture not only supports the flexible integration of a wide variety of data sources, but also guarantees data sovereignty in accordance with the principles of the International Data Spaces Association (IDSA). Semantic data integration for assessing agricultural land use intensity. Integration of diverse data sources (satelite data, soil data, agricultural statistics, research databases, socioeconomic information, model data (see Figure 22).

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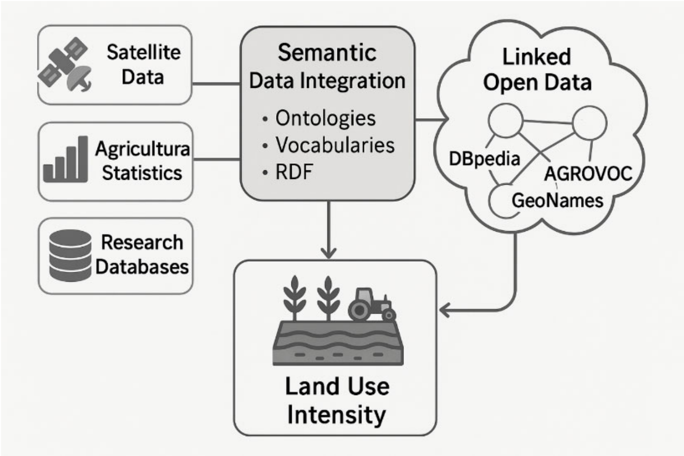

Figure 22. Semantic data integration for assessing agricultural land use intensity. Integration of diverse data sources (satelite data, soil data, agricultural statistics, research databases, socioeconomic information, model data.

6. Conclusions and Further Research

The aim of this study is to systematically improve and standardise the recording and evaluation of agricultural land use intensity (LUI). To this end, standardised indicators for the monitoring of A-LUI at various levels - Germany, Europe and worldwide (FAO, OECD, World Bank, EUROSTAT) - were first compiled. In addition, a comprehensive compilation of in-situ methods was made specifically for Germany in order to create a detailed and locally specific basis for comparison with the RS-based derivation of A-LUI.

At the core of the paper is the introduction of an RS-based definition of A-LUI based on five specific characteristics: trait LUI indicators, genesis LUI indicators, structural LUI indicators, taxonomic LUI indicators and functional LUI indicators. Numerous practical examples are used to illustrate how RS technologies can capture these characteristics. In addition, innovative approaches and modern technologies, such as RS, AI and semantic data integration, were used to improve the quantification and evaluation of A-LUI using RS.

A standardised and globally comparable assessment of A-LUI is essential for the future establishment of biodiversity credits. These credits could make a decisive contribution to financially rewarding sustainable agricultural practices and thus actively promote the protection and restoration of biodiversity

However, despite the progress made, methodological challenges remain. In particular, the indirect recording of input factors such as pesticides and fertilisers, the consideration of seasonal dynamics and small-scale structures pose obstacles. Nevertheless, RS technologies in combination with hybrid modelling and artificial intelligence (AI) offer a powerful platform for precise and sustainable monitoring of LUI

Future research should address the following aspects in greater depth:

- Integration of different RS technologies: Development of integrated multi-sensor approaches to capture specific management practices more precisely and map them in a spatially differentiated way.
- Hybrid modelling and AI-based approaches: Further development of hybrid models that combine physical radiative transfer models with data-driven methods to capture complex ecological and agricultural processes even more accurately.
- Standardisation and harmonisation: Promotion of international cooperation to standardise RS data and indicators in order to increase comparability and global applicability.

- Scaling strategies: Research into effective scaling approaches to link local, detailed in-situ data with large-scale RS data in order to develop robust models for large-scale applications.
- Sustainability assessment: Greater integration of RS-based indicators into environmental and socio-economic modelling to provide more comprehensive assessments of the sustainability and environmental impacts of agricultural intensification strategies.
- This considerably improves the informative value and practical applicability of RS-based LUI indicators and thus contributes significantly to the sustainable development of agricultural systems.

Author Contributions: A.L., F.H conceptualisation, methodology, writing—original draft preparation, writing—review and editing, visualisation, J.B.supervision; P.S., J.B., M.P.; T.Z. investigation, resources, visualisation, writing—review and editing P.S., J.B., M.P; T.Z. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: No data were integrated in this paper.

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Conflicts of Interest: The authors declare no conflicts of interest.

Appendix A

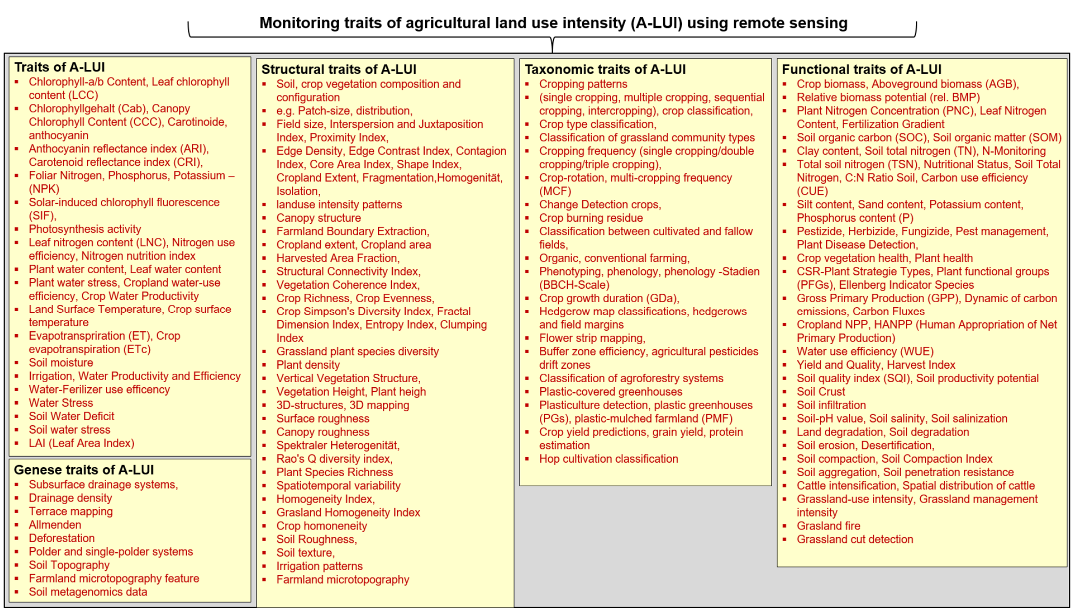

Figure A1. Monitoring the five characteristics of agricultural land use intensity (A-LUI) using RS. These are: Traits of A-LUI, Genese traits of A-LUI, Structural traits of A-LUI, Taxonomic traits of A-LUI, Functional traits of A-LUI with examples.

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Table 1A. Geographical area of monitoring, temporal availability of indicators, link, and selected examples of indicators for measuring and monitoring agricultural land use intensity; carried out by the FAO, OECD, World Bank and EUROSTAT.

	FAO	OECD	World Bank	EUROSTAT
Geographical area of monitoring	• Worldwide coverage, with a special focus on developing countries	• Primarily OECD member countries, focus on highly developed industrialised nations	• Developing countries and emerging markets	• European Union (EU) and some enlargement countries
Time availability of the indicators	• Indicators of land use intensity have been available since the 1960s, • Increased surveillance since the 1990s	• Data and analyses on land use intensity since the 1980s, • Regular reports since the early 2000s.	• Data on land use intensity since the 1990s, • Comprehensive database (WDI) since the 2000s.	• Harmonised data on agriculture and land use since the 1990s, • Regular (every three to five years) surveys since the 1990s
Link	• FAO database FAOSTAT • https://www.fao.org/statistics/data-dissemination/agrifood-systems/en, (data access: 11.07.2024)	• OECD • https://www.oecd.org/, (data access: 11.07.2024)	• World Development Indicators (WDI) • https://databank.worldbank.org/source/world-development-, (data access: 11.07.2024)	• Farm Structure Surveys (FSS) • https://ec.europa.eu/eurostat/web/microdata/farm-structure-survey (data access: 11/07/2024)
Indicators (selective examples)				
Indicator	**FAO**	**OECD**	**World Bank**	**Eurostat**
Agricultural area	Total area for agriculture (arable land, permanent grassland, permanent crops)	Agricultural land, including arable land, permanent crops, and pastures	Agricultural land (sq. km)	Utilised agricultural area (UAA)
Arable land	Land for crops, including repeatedly cultivated soils and fallow land	Arable land, including temporary crops and fallow land	Arable land (hectares)	Arable land
Permanent grassland	Land for perennial grasses and forage plants	Permanent pastures and meadows	Permanent meadows and pastures (hectares)	Permanent grassland

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Permanent crops	Land for perennial crops such as fruit trees and vineyards	Permanent crops, such as orchards and vineyards	Permanent crops (hectares)	Permanent crops
Harvest yields	Amount of crop per unit area	Crop yields, measured by specific crop outputs per hectare	Cereal yield (kg per hectare)	Crop production per unit area
Use of fertilisers	Amount of fertiliser per hectare	Fertiliser consumption (kg per hectare of arable land)	Fertiliser consumption (kg per hectare of arable land)	Consumption of fertilisers per unit area of agricultural land
Pesticide use	Amount of pesticides per hectare	Pesticide sales and usage	Pesticide consumption (kg per hectare of arable land)	Pesticide sales and consumption
Irrigated area	Proportion of artificially irrigated agricultural land	Area equipped for irrigation (hectares)	Irrigated land (% of total agricultural land)	Irrigated area
Machine inventory	Number and type of machines per unit area	Agricultural machinery, such as tractors per hectare	Agricultural machinery (tractors per 100 sq. km of arable land)	Number of tractors and other agricultural machinery per unit area of agricultural land
Labour input	Labour hours per unit area	Labour input in agriculture, measured by hours worked per hectare	Employment in agriculture (% of total employment)	Labour force in agriculture
Livestock density	Number of animals per unit area of pastureland	Livestock density, measured as livestock units per hectare of pasture land	Livestock production index	Livestock density per unit area of pasture land
Carbon sequestration in the soil	Amount of carbon sequestered in the soil	Soil organic carbon content	Soil organic carbon content	Soil organic carbon content
Ground cover	Type and extent of ground cover	Land cover types and changes	Land cover (% of land area)	Land cover and land use
Erosion risk	Risk of soil erosion due to water or wind	Soil erosion rates	Soil erosion rates	Soil erosion and degradation risk
Biodiversity	Diversity of plant and animal	Farmland biodiversity indices	Agricultural biodiversity	Biodiversity indicators in agricultural

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	species on farmland land (eg. Farmland birds, pollinators, butterflies)	(eg. Farmland birds, pollinators, butterflies)	indices (eg. Farmland birds, pollinators, butterflies)	landscapes (eg. Farmland birds, pollinators, butterflies)
Water consumption in agriculture	Amount of water used for irrigation	Agricultural water withdrawal	Agricultural water withdrawal (% of total water withdrawal)	Water use in agriculture
Agricultural production per unit of input	Efficiency of the means of production in agriculture	Total factor productivity in agriculture	Agricultural value added per worker	Output per hectare of agricultural land
Energy consumption in agriculture	Energy consumption in agriculture	Energy use in agriculture	Energy use in agriculture	Energy consumption in agriculture
Sustainability indicators	Sustainability of agricultural practices	Sustainable agriculture practices indicators	Sustainable land management indicators	Sustainable farming practices
Climate impact of agriculture	Greenhouse gas emissions from agriculture	Greenhouse gas emissions from agriculture	Agricultural methane emissions (kt of CO2 equivalent)	Greenhouse gas emissions from agriculture
Nutrient balance in the soil	Balance of nitrogen and phosphorus in the soil	Nitrogen and phosphorus balance	Soil nutrient balance	Nutrient balance in agricultural soils
Bioproductivity	Productivity of biological systems on agricultural land	Biological productivity of agricultural systems	Agricultural productivity indexes	Biological productivity of agricultural lands
Plant protection measures	Measures to combat pests and diseases	Pest and disease control practices	Pest and disease control indicators	Plant protection measures and their impact
Energy efficiency in agriculture	Efficiency of energy consumption in agriculture	Energy efficiency in agricultural practices	Energy productivity in agriculture	Energy efficiency indicators in farming
Utilisation of genetic resources	Utilisation and conservation of genetic resources in agriculture	Use and conservation of genetic resources	Genetic resource management indicators	Conservation and use of agricultural genetic resources

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Landscape diversity	Diversity of landscapes and agroecosystems	Landscape diversity and heterogeneity	Landscape diversity indicators	Landscape heterogeneity and diversity in agricultural areas
Soil compaction	Degree of soil compaction caused by agricultural machinery	Soil compaction indicators	Soil compaction risk	Soil compaction due to agricultural practices
Waste management in agriculture	Handling agricultural waste	Agricultural waste management practices	Waste management in agriculture	Management and recycling of agricultural waste
Soil moisture	Moisture content of the soil	Soil moisture levels	Soil moisture content indicators	Soil moisture monitoring in agricultural lands
Landscape fragmentation	Fragmentation of natural and agricultural landscapes	Landscape fragmentation and its impact on agriculture	Landscape fragmentation indexes	Impact of landscape fragmentation on agriculture
Sustainable land use practices	Spreading sustainable agricultural practices	Adoption of sustainable agricultural practices	Sustainable land management practices	Implementation of sustainable farming practices
Water utilisation efficiency	Efficiency of water utilisation in agriculture	Water use efficiency in agricultural practices	Agricultural water productivity	Water use efficiency in irrigated agriculture
Agroecological indicators	Indicators for the assessment of agroecological systems	Agro-ecological assessment indicators	Agro-ecological practices	Assessment of agro-ecological systems
Erosion due to wind	Loss of topsoil due to wind erosion	Wind erosion rates	Wind erosion indicators	Impact of wind erosion on agricultural land
Soil fertility	Level of soil fertility and its changes	Soil fertility levels	Soil fertility indicators	Changes in soil fertility
Land use changes	Changes in the utilisation of agricultural land	Changes in agricultural land use	Land use change indicators	Agricultural land use changes
Irrigation efficiency	Efficiency of irrigation methods	Irrigation efficiency	Efficiency of irrigation systems	Efficiency of water use in irrigation systems
Climate adaptation measures	Measures to adapt to climate change	Climate adaptation practices in agriculture	Climate resilience indicators	Implementation of climate adaptation

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				measures in agriculture
Resource utilisation efficiency	Efficient use of natural resources	Resource use efficiency in agriculture	Resource productivity indicators	Efficiency of resource use in agriculture
Soil acidification	Degree of soil acidification and its causes	Soil acidification levels	Soil pH indicators	Impact of acidification on agricultural soils
Soil salinisation	Level of soil salinisation and its effects	Soil salinisation rates	Soil salinity indicators	Effects of salinisation on agricultural productivity
Utilisation of renewable energies	Share of renewable energies in agriculture	Renewable energy use in agricultural practices	Share of renewable energy in agriculture	Use of renewable energy sources in farming
Environmentally friendly cultivation methods	Spreading environmentally friendly cultivation methods	Adoption of eco-friendly farming practices	Eco-friendly agricultural practices	Implementation of environmentally friendly farming methods
Economic sustainability	Economic viability of farms	Economic sustainability of agricultural holdings	Economic viability indicators	Economic sustainability of farms
Social sustainability	Social aspects of agricultural practice	Social sustainability in agriculture	Social indicators in rural areas	Social impacts of agricultural practices
Productivity per unit area	Productivity of agricultural land	Land productivity indicators	Productivity of agricultural land	Output per unit of agricultural area
Water quality indicators	Impact of agriculture on water quality	Impact of agriculture on water quality	Water quality in agricultural areas	Effects of agricultural runoff on water quality
Infrastructure for agriculture	Availability and quality of agricultural infrastructure	Agricultural infrastructure development	Infrastructure investment in agriculture	Quality and accessibility of agricultural infrastructure
Innovation in agriculture	Implementation of new technologies and processes	Agricultural innovation and technology adoption	Innovation indicators in agriculture	Adoption of new agricultural techn

Table A2. High spatial resolution satellite missions, sensor/type, spatial resolution, spectral bands/type, availability, launch date and operator.

Satellit / Mission	Sensor / Typ	Spatial resolution	Spectral bands / Sensor typ	Availability	Start date	Operator of the satellite mission
WorldView-3	Visible (PAN+MS+SWIR)	0,31 m (PAN), 1,24 m (MS)	Panchromatic Multispectral SWIR	Commercial	2014	Maxar
WorldView-2	Optically	0,46 m (PAN), 1,84 m (MS)	Panchromatic Multispectral	Commercial	2009	Maxar
GeoEye-1	Optically	0,41 m (PAN), 1,65 m (MS)	Panchromatic Multispectral	Commercial	2008	Maxar
Pleiades Neo	Optically	0,3 m (PAN), 1,2 m (MS)	Panchromatic Multispectral	Commercial	2021+	Airbus
Pleiades 1A/1B	Optically	0,5 m (PAN), 2,0 m (MS)	Panchromatic Multispectral	Commercial	2011/2012	Airbus
SkySat	Optically + Video	0,5–0,8 m (PAN), 1–2 m (MS)	RGB, NIR, Video	Commercial	2013+	Planet
BJ-3B (SuperView-2)	Optically	0,3 m (PAN), 1,2 m (MS)	Panchromatic Multispectral	Commercial	2022	21AT (China)
Capella Space	RADAR (X-Band SAR)	0,3–0,5 m (Spotlight)	SAR	Commercial	2018+	Capella Space (USA)
ICEYE	RADAR (X-Band SAR)	0,25–1 m	SAR	Commercial	2018+	ICEYE (Finnland)
TerraSAR-X	RADAR (X-Band SAR)	bis 1 m (Spotlight-Modus)	SAR	Commercial / Scientifically free	2007	DLR / Airbus
PAZ	RADAR (SAR)	1 m	SAR (X-Band)	Commercial	2018	Hisdesat (Spain)
Sentinel-1A/B	RADAR (C-Band SAR)	10 m	SAR	Freely available	2014/2016	ESA / Copernicus
Drohnen / UAV	Optically + Multispectral	< 0,1 m	RGB, Multispectral, Hyperspectral, LiDAR	Own operation		User-based
Aerial photos	Optically	0,20cm	Orthophotos (DOP)	Commercial / Authorities		Federal states, Federal

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	True Orthophotos, RGB, CIR	and partly scientific free	Agency for Cartography and Geodesy

Here is a comprehensive table summarising the various indicators for measuring agricultural land use intensity and landscape structure that can be measured using RS:

Table A3. Various indicators for measuring agricultural land use intensity that can be detected using RS. Here is a comprehensive table summarising the various indicators for measuring agricultural land use intensity and landscape structure that can be measured using RS:.

Indikator	Satelliten	Reference
Trait diversity of LUI		
Chlorophyll-a/b Content Leaf chlorophyll content (LCC) Chlorophyllgehalt (Cab) Canopy Chlorophyll Content (CCC) Carotinoide, anthocyanin Anthocyanin reflectance index (ARI) Carotenoid reflectance index (CRI)	Sentinel-1[1], Sentinel-2[1], Landsat 8[1], CRIME[1,] , EnMAP[1], Airborne hyperspectral CASI[2], Airborne Visible/ Infrared Imaging Spectrometer AVIRIS[2], Airborne HyMap[2], UAV-(HSP,MSP)[3], Handheld portable hyperspectral camera (Specim IQ) ASD[4], Laboratory spectroscopy[5]	[87,88,252–259,94,97,110,247–251]
Foliar Nitrogen, Phosphorus, Potassium - NPK	UAV (LiDAR, MSP) [3], SVC HR-1024i spectrometer ASD[4]	**[87,260,261]**
Solar-induced chlorophyll fluorescence (SIF), **Photosynthesis activity**	Sentinel-3[1], GOSIF data[1], AS-SpecFOM (Ground based)[6], FluoSpec2 system (Ground based)	[72,99,262–265]
Leaf nitrogen content (LNC) Nitrogen use efficiency, Nitrogen nutrition index	Sentinel-2[1], CRIME[1], PRISMA[1],Airborne micro-hyperspec NIR-100 camera[2], UAV	[87,88,90,111,112,266,267]
Plant water content Leaf water content Plant water stress Cropland water-use efficiency Crop Water Productivity	GLASS[1], Landsat[1], Sentinel-2[1], UAV (MSP, HSP)[3], mmWave RADAR (Tower)[6], Cropland ecosystem flux sites[6], Local TIR Sensor[6],	[268–276]
Land Surface Temperature Crop surface temperature	Landsat[1], High Spatio-Temporal Resolution Land Surface Temperature Monitoring (LSTM) Mission[1], UAV (TIR, RGB, MSP)[3]	[272,277–281]
Evapotranspriration (ET) Crop evapotranspiration (ETc)	MODIS[1], DEIMOS-1 is a commercial tasking EO satellit[1], Landsat[1], Sentinel-2[1], SuperDove satellites (PlanetScope)[1], UAV-(RGB, MSP, TIR)[3]	[282–290]

Soil moisture	MODIS-Terra¹, Landsat¹,AMSR-2¹,AMSR-E¹, NISAR¹, Sentinel-1¹, Sentinel-2¹, SMAP¹, Airborne hyperspectral (DAIS)², Airborne hyperspectral (AISA Eagle, Hawk) ²	[291–299]
Irrigation Irrigation Efficiency Water Productivity and Efficiency Irrigation patterns Water-Ferilizer use efficency Water Stress Soil Water Deficit Soil water stress	MODIS¹, Landsat¹, Sentinel-2¹, UAV (MSP)³, ASD⁴,	[300,301,310,311,302–309]
LAI (Leaf Area Index)	MODIS¹, Landsat¹, Sentinel-2¹, UAV-(HSP, TIR, LiDAR)³, Ocean Optics USB2000 (Tower)⁶	[255,256,312–314]
Genese Trait Diversity of LUI		
Subsurface drainage systems, Drainage density	RADAR (SAR)¹, Landsat¹, Senitnel-2¹, Airborne LiDAR², Airborne data², UAV – RGB, CIR, TIR³	[124–128,315,316]
Terrace mapping	Landsat¹, Sentinel-1¹, Sentinel-2¹, GF-2 satellite image¹, WorldView-1¹, WorldView-3¹, Airborne LiDAR², UAV-LiDAR³	[129–131,136–138]
Allmenden	Airborne LiDAR³	[139,140]
Deforestation	MODIS¹, ALOS PALSAR data¹, RADARSAT-2¹, Landsat¹, Sentinel-1¹, Sentinel-2¹, UAV (RGB, NIR, IRT)³	[143–147,317–320]
Polder and single-polder systems	Google Earth RS data¹, Corona spy satellite imagery¹	[321,322]
DEM (Digital Elevation Model) DSM (Digital Surface Model)	SRTM¹, TerraSAR-X¹, TanDEM-X¹, Sentinel-1¹, Sentinel-3¹, ALOS-2 PALSAR-2¹, ALOS PRISM¹, Terra ASTER¹, ICESat GLAS¹, Airborne LiDAR², UAV (SAR, RGB)³	[61,323,332–335,324–331]
Soil Topography Farmland microtopography feature	Landsat¹, Sentinel-1¹, Sentinel-2¹, CORONA KH-4B¹, Gaofen-7 satellite¹, Airborne LiDAR²	[166,336–340]
Soil metagenomics data	UAV (MSP, LiDAR)³	[341]
Structural traits of LUI		
Soil, crop vegetation composition and configuration (e.g. Patch-size, distribution	MODIS¹, Landsat¹, Spot¹, Sentinel-2¹, WorldView-2/-3¹, QuickBird¹, Pleiades¹, GeoEye¹, GF-2¹,	[31,33,344–353,67,354–356,148,149,156,157,266,342,343]

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Field size, Interspersion and Juxtaposition Index, Proximity Index, Edge Density, Edge Contrast Index, Contagion Index, Core Area Index, Shape Index, Cropland Extent, Fragmentation,Homogenity, Isolation, Landuse intensity patterns, Canopy structure Farmland Boundary Extraction, Cropland extent, Cropland area, Harvested Area Fraction, Structural Connectivity Index, Vegetation Coherence Index, Crop Richness, Crop Evenness, Crop Simpson's Diversity Index, Fractal Dimension Index, Entropy Index, Clumping Index, Grassland plant species diversity Plant density	RapidEye[1], PlanetScope[1], Airborne Hyperspectral AVIRIS and HYDICE[2], Airborne data[2], UAV (RGB, MSP, HSP)[3]	
Vertical Vegetation Structure, Vegetation Height, Plant heigh 3D-structures, 3D mapping	GEDI LiDAR[1], ICESat-2[1], UAV (RGB, LiDAR) Phenotyping robot "MARS-PhenoBot"[6], 6-DOT robot[6], RGB-Camera[6], Terrestrial LiDAR[6]	[357–362]
Surface roughness Cnopy roughness	Sentinel-1[1], MODIS[1], UAV (RGB)[3]	[162–164]
Spektraler Heterogenität, Rao's Q diversity index, Plant Species Richness Spatiotemporal variability	MODIS[1], Landsat[1], Sentinel-2[1]	[160,161,363]
Homogeneity Index, Grasland Homogeneity Index Crop homoneneity	Sentinel-1[1], Sentinel-2[1], GF-2[1]	[364–366]
Soil Roughness, Soil texture, Farmland microtopography	Landsat[1], Sentinel-1[1], Sentinel-2[1], AHSI/ZY1-02D satellite[1], SRTM[1], Airborne LiDAR[2], ASD Handspectometer[4], Smartphone-captured digital images[6]	[166,167,374,375,340,367–373]
Taxonomic LUI		
Cropping patterns	MODIS[1], Spot[1], Landsat[1], **Sentinel-1**[1], Sentinel 2[1], IRS[1], WiFS[1], Airborne	**[150,168,177,178,181,376,377,169–176]**

(single cropping, multiple cropping, sequential cropping, intercropping)	AVIRIS[2], **RADARSAT-2**[1], Airborne LiDAR[2]	
Crop classification, Crop type classification Crop type mapping	MODIS[1], Landsat[1], Sentinel-1[1], Sentinel-2[1], Sentinel-3[1], Airborne AVIRIS[2], UAV (HSP)[3]	[135,151,182,378–384]
Classification of grassland community types	Landsat[1], Sentinel-1[1], Sentinel-2[1]	[385–387]
Cropping frequency (single cropping/double cropping/triple cropping) Crop-rotation Multi-cropping frequency (MCF) Croping intensity Cropping intensity index Change Detection crops	MODIS[1], Gaofen-1[1], GF-1[1], Landsat[1], Sentinel-1[1], Sentinel-2[1]	[169,183,394–397,349,377,388–393]
Crop residue cover mapping	Landsat[1], Sentinel-2[1], Google Earth Engine[1], UAV[3], FieldSpec Pro[4], Photo analysis surveys[6]	[398–403]
Crop burning residue	MODIS[1], AVHRR[1], LISS-III[1], LISS-IV[1], UAV[3]	[404–406]
Classification between cultivated and fallow fields	MODIS[1], Landsat[1], Sentinel-2[1]	[376,388,407–409]
Organic, conventional farming Organic and non-organic farming	Landsat[1], Spot[1], Sentinel-2[1], KOMPSAT-2[1], WorldView-2[1], UAV (RGB)[3], Hyperspectral ASD[4]	[410–413]
Phenotyping, Phenology, Phenology-Stadien (BBCH-Scale)	UAV (RGB, MSP, HSP, TIR, LiDAR)[3], UAV (RGB, VIS, NIR, TIR, LiDAR)[3], Labor-Hyperspectral – AISA-EAGLE[5]	[252,312,335,414–419]
Crop growth duration (GDa),	MODIS[1], Landsat[1], Gaofen-1[1], Sentinel-2[1], RapidEye[1], UAV (SAR)[2]	[394,420–423]
Hedgerow map classifications, Hedgerows and field margins	TerraSAR-X[1], Spot[1], IKONOS[1], Airborne MSP[2], Aerial photographs[2], UAV (RGB, MSP)[3]	[424–429]
Flower strip mapping Flower Mapping	Airborne Hyperspectral (HySPEX, RGB, TIR)[2], Airborne Hyperspectral (AISA-Eagle)[2], Airborne MSP[2], UAV (MSP, HSP)[3]	[429–434]
Buffer Zone Efficiency Agricultural Pesticides Drift zones	Landsat[1], Sentinel-2[1]	[435]

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Classification of agroforestry systems	RapidEye[1], PlantetScope[1], LISS IV[1], Sentinel-2[1]	[436–440]
Plastic-covered greenhouses Plasticulture detection Plastic greenhouses (PGs) and Plastic-mulched farmland (PMF)	Landsat[1], Sentinel-1[1], Sentinel-2[1], GF-2	[441–445]
Crop yield predictions Grain Yield, Protein estimation	MODIS[1], Landsat[1], Sentinel-2[1], UAV – (MSP, HSP)[3]	**[266,446,455,447–454]**
Hop cultivation classification	UAV (MSP)[3], Mobile phone camera[6]	**[456,457]**
Functional traits of LUI		
Crop biomass, Aboveground biomass (AGB), Relative biomass potential (rel. BMP)	MODIS[1], Landsat[1], Sentinel-1[1], Sentinel-2[1], PlanetScope[1], UAV (MSP, RGB)[3], Smartphone[6]	[188–194,301,458]
Plant Nitrogen Concentration (PNC) Leaf Nitrogen Content Fertilization Gradient	Sentinel-2[1], UAV (MSP, TIR)[3]	[94,203–205,459–461]
Soil organic carbon (SOC) Soil organic matter (SOM)	ALOS-2[1], PALSAR-2[1], Landsat[1], Spot 4/5[1], GF-1[1], RADAR (PLAS)[1], Sentinel-1[1], Sentinel-2[1], Sentinel-3[1], Airborne hyperspectral (DAIS)[2], Airborne hyperspectral (AISA Eagle, Hawk)[2], Hyperspectral APEX[2,] UAV (SAR)[3], VIS–NIR spectroscopy (Field)[1],	[208,213,465–474,214,219,221,222,299,462–464]
Clay content	Landsat[1], Aster[1], Sentinel-2[1], Airborne hyperspectral (AISA Eagle, Hawk)[2]	[375,475–481]
Soil total nitrogen (TN) N-Monitoring Total soil nitrogen (TSN) Nutritional Status Soil Total Nitrogen Soil Nutrients Contents	Sentinel-1[1], Sentinel-2[1], GF-1[1], UAV (HSP, MSP, TIR)[3], ASD (Field)[4]	[206,213,488,469,480,482–487]
C:N Ratio Soil	Landsat[1], Sentinel-1[1], Sentinel-2[1], Sentinel-3[1]	[222,468,489–492]
Carbon use efficiency (CUE)	MODIS[1], Landsat[1], Sentinel-2[1]	[493–496]
Silt content	GF-1[1], Airborne hyperspectral (AISA Eagle, Hawk)[2],	[375,497]
Sand content	Landsat[1], Sentinel-2[1], Aster[1], GF-1[1], Planet/NICFI[1], Airborne hyperspectral (AISA Eagle, Hawk)[2]	[375,481,497–501]
Potassium content	PRISMA[1], UAV (MSP)[3]	[484,485]

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Phosphorus content (P)	MODIS[1], Landsat[1], Sentinel-2[1], PRISMA[1], UAV (MSP, LiDAR)[3], ASD[4]	[341,484–487,502]
Pestizide, Herbizide, Fungizide Pest management	Sentinel-2[1], UAV[3], Local hyperspectral camera[6], ASD - LeafSpec hyperspectral images[4]	[195–200,503,504]
Plant Disease Detection, Crop vegetation health Plant health	Sentinel-1[1], Sentinel-2[1], UAV (RGB, MSP, VIS, NIR, TIR, LiDAR)[3], ASD FieldSpec Pro FR[4]	[97,202,511–516,411,416,505–510]
CSR-Plant Strategie Types Plant functional groups (PFGs) Ellenberg Indicator Species	Landsat[1], Sentinel-2[1], Airborne hyperspectral data (AISA dual)[2], Airborne AISA Fenix[2], Airborne imaging spectrometer APEX[2], Airborne hyperspectral HySpex[2]	[517–524]
Gross Primary Production (GPP) Dynamic of carbon emissions, Carbon Fluxes	MODIS[1], Meris[1], Landsat[1], Sentinel-1[1], Sentinel-2[1], Sentinel-3[1], Hyperspectral Ocean Optics USB2000 (Tower)[6], LEDAPS-Aerosol Robotic Network (AERONET)[6]	[254,493,525–532]
Cropland NPP	MODIS[1], Landsat[1], UAV (MSP)[3]	[149,314,493,533–538]
HANPP (Human Appropriation of Net Primary Production)	MODIS[1], Landsat[1], Sentinel-2[1]	[539–543]
Water use efficiency (WUE)	MODIS[1], Landsat[1], Sentinel-1[1], Sentinel-2[1]	[493,544–548]
Yield and Quality	Landsat[1], Sentinel-1[1], Sentinel-2[1], UAV (MSP)[3]	[193,531,549–556]
Harvest Index	MODIS[1], HJ-1 satellite[1], Sentinel-2[1], UAV (HSP)[3], FieldSpec HandHeld Spectroradiometer (ASD)[4]	[557–560]
Soil quality index (SQI)	Landsat[1], Sentinel-2[1], Airborne hyperspectral (AISA)[2]	[338,561,562]
Soil productivity potential	MODIS[1], Landsat[1], Sentinel-2[1], ASD FieldSpec[4]	[310,480,563–565]
Soil Crust	KOMPSAT-2 satellite[1], Airborne hyperspectral (DAIS)[2], Airborne hyperspectral (AISA Eagle, Hawk)[2], UAV (RGB, MSP, HSP)[3], ASD Fieldspec[4]	[299,566–572]
Soil infiltration	Airborne hyperspectral (DAIS)[2], Airborne hyperspectral (AISA Eagle, Hawk)[2], Airborne CASI-1500[2], SASI-600[2], Airborne TASI-600 hyperspectral sensors[2], UAV (HSP, Cubert UHD-185)[3]	[299,573,574]

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Soil-pH value	PALSAR-1/2[1], SRTM[1], Landsat[1], PlantetScope[1], Sentinel-1[1], Sentinel-2[1], UAV (MSP)[3], ASD FieldSpec[4]	[298,368,582–585,555,575–581]
Soil salinity Soil salinization	Landsat[1], RADAR[1], Airborne LiDAR[2], HJ-1 Hyperspectral Imager Data[2]	[298,586–593]
Land degradation, Soil degradation, Soil erosion Desertification	Landsat[1], SRTM[1], Sentinel-1[1], Sentinel-2[1], RapidEye[1], Airborne hyperspectral (DAIS)[2], Airborne hyperspectral (AISA Eagle, Hawk)[2], UAV (RGB)[3]	[299,594–599]
Soil compaction Soil Compaction Index Soil aggregation Soil penetration resistance	Landsat[1], GoogleEarth aerial imagery[1], Sentinel-2[1], RapidEye[1], Airborne hyperspectral (CASI)[2], UAV (RGB, SAR, LiDAR, MSP, TIR)[3]	[595,600–607]
Cattle intensification, Spatial distribution of cattle	Sentinel-1[1], Sentinel-2[1]	[608]
Grassland-use intensity Grassland management intensity	Landsat[1], Sentinel-1[1], Sentinel-2[1], RapidEye[1],	[184,187,609–613]
Grasland fire	MODIS[1], Sentinel-1[1], Sentinel-2[1], GF-6 WFV[1], UAV[3]	[614–618]
Grassland cut detection	SAR[1], Sentinel-1[1], Sentinel-2[1]	[619–621]
Different Water quality indicators	All RS Sensors with all RS characteristics (MSP, HSP, TIR, RADAR, LiDAR)	[63]

The sensor is used on the RS platform: 1 - spaceborne RS platforms, 2 - airborne RS platform, 3-UAV, 4- Handheld portable hyperspectral camera (Specim IQ) ASD, 5-Laboratory spectroscopy, 6-Tower, Smartphone, Ground based.

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