A Review on Applications and Utility of Remote Sensing and Geographic Information Systems

Abstract

Remote sensing, global positioning systems (GPS), geographic information systems (GIS) and the Internet of Things are emerging technology. The Internet of Things (IoT), Big Data analysis and artificial intelligence (AI) are all promising techniques that are being used to help solve problems, improve agricultural operations and inputs with the goal of increasing output while lowering costs. Over the past five decades, satellite remote sensing has become indispensable in understanding the Earth and atmospheric processes. Satellite sensors have the capability of providing data at global scales, which is economical compared to the ground or airborne sensor acquisitions. The science community made significant advances over recent years with the help of satellite remote sensing. In view of these efforts, the current review aims to present a comprehensive review of the role of remote sensing in assessing various water security issues and other application. Operational large agricultural applications include crop production forecasting, drought assessment, cropping system analysis, horticultural assessment and development, crop intensification, site suitability analysis, satellite agro-meteorology, precision farming, crop insurance, etc. This paper discusses these applications, along with possible gap areas in space observation and way forward.

Key words- Remote sensing, Geographic information systems, Satellite sensors and precision farming.

Introduction

In many developing as well as developed countries, agriculture provides food and fiber, which are fundamental for human survival [1,2]. The World Summit on Food Security proclaimed that by 2050, "the world's population is expected to double."Growing economies will boost agricultural demand by some 50% as compared to 2013 (FAO, 2017). Mechanical changes over the past century, such as the Green Revolution, have changed the look of agriculture [3]. The third agricultural revolution or Green Revolution, during the 1960s–1980s, was marked by high yield crop varieties, use of synthetic fertilizers, pesticides and a water system, which increased productivity of crops and food security, particularly in developing countries [4]. Therefore, in spite of the doubling of the global population and the tripling of food demand since the 1960s, agriculture has been able to meet the demand only by expanding its cultivated area by 30% [4,5]. The demand for food and agricultural products will continue to grow by another 30% by 2050 and more than 70% by 2050 [6]. As arable land is limited, a significant part of this increase in demand will be met through agricultural intensification, which will increase fertilizer, pesticide, water, and other inputs. Agriculture is currently undergoing a fourth revolution, aided in large part by advancements in information and communication technologies [7]. Remote sensing, global positioning systems (GPS), geographic information systems (GIS) and the Internet of Things are just a few examples of emerging technology. The Internet of Things (IoT), Big Data analysis and artificial intelligence (AI) are all promising techniques that are being used to help solve problems, improve agricultural operations and inputs with the goal of increasing output while lowering costs [8,9,10], yield losses Cloud computing and wireless sensors are used in a variety of IoT technology solutions. Smart farming activities including automated wireless-controlled irrigation systems and intelligent disease and pest monitoring and forecasting systems have been developed with the help of networks and big data analysis [9,10]. For automated and exact administration of water, fertiliser, herbicides, and insecticides, AI approaches such as machine learning (e.g., artificial neural networks) have been utilised to estimate ET, soil moisture, and crop projections [11]. Farmers can use these technologies and techniques to assess geographic variability (e.g., soils) among farms and big crop fields, which has a detrimental impact on crop growth and yields [11]. Due to the high spatial/spectral/radiometric/temporal resolutions required for PA applications, remote sensing systems that use information and communication technologies typically create a substantial volume of spectrum data. To extract meaningful information from the vast volume of data, emerging data processing techniques including Big Data analysis, artificial intelligence, and machine learning have been used [12]. "The world's population is predicted to expand to about 10 billion by 2050, boosting agricultural demand - in a scenario of modest economic growth - by some 50% compared to 2013," according to the World Summit on Food Security (FAO, 2017). However, any rise in food production must be complemented with a sustainable agricultural land management strategy to prevent or at least mitigate negative effects on water and soil quality and quantity, land degradation, greenhouse gas emissions, and biodiversity (Gomiero et al., 2011). Agriculture monitoring via remote sensing is a vast subject that has been widely addressed from multiple perspectives, sometimes based on specific applications (e.g. precision farming, yield prediction, irrigation, weed detection), specific remote sensing platforms (e.g. satellites, Unmanned Aerial Vehicles –UAV-, Unmanned Ground Vehicles –UGV-), sensors (e.g. active or passive sensing, wavelength domain, spatial sampling), or specific locations and climatic conditions. The expanding amount of published literature demonstrates that remote sensing for agriculture has acquired a certain degree of understanding and that interest in agricultural applications is increasing at an exponential rate, particularly after 2013. This growing literature also reflects significant advancements in relevant technology, such as numerous sensors with unprecedented spatial, temporal, and spectral capacities (e.g. Sentinels, Gaofen), the introduction of small new platforms such as nano-satellites or unmanned aerial vehicles (UAV), and the deployment of cloud computing and machine learning techniques. These advancements in technology should enable remote sensing in agriculture to achieve long-term goals. To understand climate change and its effects, to sustain economic development, to correctly manage natural resources, to encourage conservation, to preserve biodiversity, and to increase scientific understanding of ecosystems, reliable observations of the terrestrial environment are critical (Herold et al. 2006). Because of its capacity to offer synoptic and recurring observations of the vegetation cover, satellite remote sensing has long been regarded an appropriate technique for land use/land cover monitoring and mapping (Franklin and Wulder 2002). Since the late 1980s, there has been a greater focus on the utilisation of coarse resolution optical data, primarily the Advanced Very High Resolution Radiometer (AVHRR) images from the National Oceanic and Atmospheric Administration (NOAA). For all land portions of the world, the AVHRR was initially accessible at an 8 km resolution and later at a notional resolution of 1 km. The cost of data has steadily lowered (particularly for research purposes), and certain data is now available for free via direct broadcast. The launch of new satellite sensors such as the SPOT 4 VEGETATION (VGT) (Saint 1992), the Moderate Resolution Imaging Spectro radiometer (MODIS) (Salomonson et al. 1989,)

Precision Agriculture Using Remote Sensing Systems

Remote sensing systems for PA and agriculture in general can be divided into two categories: sensor platform and sensor type. Satellites, aerial platforms, and ground-based platforms are common places for sensors to be deployed. Satellite technology has been widely employed for PA since the 1970s. Aircraft and unmanned aerial vehicles (UAVs) have recently been employed in PA. Hand-held, free-standing in the field, and mounted on tractor or farm gear are the three types of ground-based platforms used for PA. In comparison to aerial or satellite-based platforms, ground-based systems are also known as proximal remote sensing systems since they are placed close to the target surface (land surface or plant). The geographical, spectral, radiometric, and temporal resolution of sensors employed for remote sensing differs [13]. The size of the pixel that depicts the region on the ground defines the spatial resolution of a sensor. Sensors with a high spatial resolution have a compact footprint, while sensors with a large footprint have a low spatial resolution. The sensor platform, rather than the sensor itself, can be thought of as having a high temporal resolution. The time it takes a satellite to complete an orbit and return to the same observation region, for example, is known as temporal resolution. The number of bands collected in a given span of electromagnetic spectrum indicates the spectral resolution of a sensor [14]. Hyperspectral images have a large number of infectious bands of narrow width (20 nm) separated by minor wavelength increments [15]. To minimise the dimensionality of hyperspectral data and extract meaningful information on crop conditions, a variety of vegetation indices, statistics and machine learning algorithms, such as deep convolutional neural network and random forest, have been used [16–18]. More recently, hyperspectral image quantification of solar-induced chlorophyll fluorescence (SIF) has been used to quantify photosynthesis, plant nutrients, and biotic and abiotic stressors such as disease and water stress [16–21]. Despite the fact that many contemporary satellites produce images with high spatial (5 m) and temporal (day) resolution, most publicly available satellite products are too coarse for many PA applications. The appropriate spatio-temporal resolution necessary for PA is determined by various aspects, including management objectives, field size, and farm equipment's ability to alter input application rates (irrigation, fertiliser, pesticide, etc.). In comparison to variable rate fertiliser and irrigation (5–10 m) applications, crop biomass and yield estimation often require higher spatial resolution (1–3 m) [22]. Sensors onboard satellites, aeroplanes, and unmanned aerial vehicles (UAVs) are often passive sensors, meaning they don't have their own light source. However, some spacecraft, such as the ERS-1/2's active microwave instrument (AMI), have active sensors onboard. Active proximity sensors are found on many ground-based remote sensing devices. Active proximity sensors are used in commercially available variable fertiliser rate application systems like Green Seeker and Crop Circle.

Variations in daylight have the least impact on observed reflectance in such systems, resulting in more accurate and repeatable normalised difference vegetation index (NDVI) or other vegetation indices (VI) for crop nutritional status monitoring. Other sensors placed on subsequent satellites (thermal infrared and microwave) are increasingly being used in agriculture. Thermal infrared sensors monitor the energy released by a target (such as crops) to assess its temperature, which can then be used to calculate crop water stress, ET, and irrigation needs [23]. Microwave sensors measure the radiated energy (although in longer microwave wavelengths) from the ground surface in the same way that thermal sensors do. Microwave sensors are mostly used to determine soil moisture content and crop water use over wide areas [24]. Microwaves can also penetrate clouds, which gives them an edge over other types of sensors that use visible and near-infrared wavelengths.

Remote Sensing Applications in the Past

Researchers have long recognised the need of mapping soil and land use databases for long-term natural resource management at the local, regional, and national levels [25, 26]. Designing and implementing irrigation, drainage, fertiliser, and other crop management strategies, which are fundamental components of PA, requires knowledge of soil physical, biological, and chemical features. Similarly, land use mapping can be used to examine the regional to national consequences of current management and policy. Even before the phrase "remote sensing" was coined in 1958, a conventional strategy of utilise remote sensing techniques in agriculture existed [27]. During the 1930s and 1940s, aerial photography was used to map soils, land usage, and agricultural conditions in the United States [28]. However, traditional soil mapping and land use classification approaches (such as low altitude photography and ground crews) often include considerable fieldwork and laboratory examination, which are both costly and time-consuming [29, 30]. Later years saw the introduction of satellite remote sensing, allowing for more efficient and effective mapping of land use and land cover at regional, national, and global scales. The launch of Vanguard 2 and TIROS 1 in 1959 and 1960, respectively, marked the beginning of meteorological satellite remote sensing [31]. The National Aeronautics and Space Administration launched Landsat 1 (previously known as the Earth Resources Technology Satellite—ERTS) on July 23, 1972, ushering in a new age of satellite remote sensing for agriculture (NASA). The Landsat programme is jointly managed by NASA and the US Department of the Interior's US Geological Survey (USGS). Following Landsat 1, a succession of Landsat satellites (Landsat 2–8) were launched to offer academics, land managers, and policymakers with high-quality photographs to aid in the global management of natural resources (Table 1)

Table 1. List of satellite sensors used in precision agricultural (PA)

Satellite (Years Active)	Sensor (Spatial Resolution)	Temporal Resolution	Application in Precision Agriculture
Landsat 1 (1972–1978)	MS (80 m)	18 days	Crop growth [32]
AVHRR (1979–present)	MS (1.1 km)	1 day	Nutrient management [33]
Landsat 5 TM (1984–2013) Landsat 7 (1999–present) Landsat 8 (2013–present)	MS and Thermal (60 m–Landsat 7,100 m–Landsat 8, 120 m–Landsat 5)	16 days	Biomass [34]; crop yield [35]; crop growth [36]
SPOT 1 (1986–1990) SPOT-2 (1990–2009)	MS (20 m)	2–6 days	Water management [37]
IRS 1A (1988–1996)	MS (72 m)	22 days	Water management, nutrient management [38]
LiDAR (1995)	VIS (10 cm)	N/A	Topography, nutrient management [39]
RadarSAT (1995–2013)	C-band SAR (30 m)	1–6 days	Crop growth [40]
IKONOS (1999–2015)	MS (3.2 m)	3 days	Crop yield [41]; soil properties [42]; nutrient management [33]; ET estimation [43]

EO-1 Hyperion (2000–2017)	HS (30 m)	16 days	Disease [44,45]
Terra/Aqua MODIS (Terra-1999–present, Aqua-2002–present)	MS (Spectro Radiometer; 250–1000 m)	1–2 days	Crop yield [46]; crop growth [47]
Terra-ASTER (2000–present)	MS and Thermal (15 m–V, NIR, 30 m–SWIR, 90 m–TIR)	16 days	Water management [48]
QuickBird (2001–2014)	MS (2.44 m)	1–3.5 days	Disease [49]
AQUA AMSR-E (2002–2016)	MS (Microwave Radiometer; 5.4 km–56 km)	1–2 days	Water management [50]
Spot-5 (2002–2015)	MS (V, NIR–10 m, SWIR–20 m)	2–3 days	Crop yield [51]
ResourceSat-1 (2003–2013)	MS (5.6m–V, 23.5 m–SWIR)	5 days	Nutrient management [52]
KOMPSAT-2 (2006–present)	MS (4 m)	5.5 days	Crop yield [53]
Radarsat-2	C-band SAR (1–100 m)	3 days	LAI and biomass [54]
RapidEye (2008–present)	MS (6.5 m)	1–5.5 days	Water management [55]; crop yield [56]; crop growth and chlorophyll [57]
GeoEye-1 (2008–present)	MS (1.65 m)	2.1–8.3 days	Nutrient management [58]
WorldView-2 (2009–present)	MS (1.4 m)	1.1 days	Crop growth [59]
Pleiades-1A (2011–present) Pleiades-1B (2012–present)	MS (2 m)	1 day	Crop growth [60,61]
VIIRS Suomi-NPP (2011–present) VIIRS-JPSS-1 (2017–present)	MS (IR Radiometer, 375 m and 750 m)	16 day (repeat)	Crop management (NDVI [62])
KOMPSAT-3 (2012–present)	MS (2.8 m)	1.4 days	Crop growth [63]
Spot-6 (2012–present), Spot-7 (2014–present)	MS (6 m)	1-day	Disease [64]
SkySat-1 (2013–present) SkySat-2 (2014–present)	MS (1 m)	sub-daily	Crop growth [65]
Worldview-3 (2014–present)	SS (1.24 m)	<1 day	Crop growth [66]; weed management [58]
Sentinel-1 (2014–present)	C-band SAR (5–40 m)	1–3 days	Crop growth[65]
Sentinel-2 (2015–present)	MS (10 m–V and NIR, 20 m–Red edge and	2–5 days	Yield [66]; N management [68]

	SWIR, 60 m–2 NIR)		
KOMPSAT-3A (2015–present)	MS (V NIR–2.2 m, SWIR–5.5 m)	1.4 days	Disease [69]
SMAP (2015–present)	L-band SAR (1–3 km) and radiometer (40 km)	2–3 days	Crop yield [70]; water management [71]
TripleSat (2015–present)	MS (3.2 m)	1 day	Crop growth [72]
ECOSTRESS-PHyTIR (2018–present)	Thermal (38 × 69 m)	1–5 days	ET [73]

In many major parts of the world, satellite data from these missions was utilised to classify land use and crops. Satellite products are also used to monitor soil health, vegetation health, and hydrologic and climatic factors that are crucial for PA (e.g., soil organic carbon, soil moisture, NDVI, LAI), groundwater, and rainfall). When compared to aerial photography, which was traditionally employed for land use classification across wide areas, using satellite photos proved to be more cost-effective. However, for many PA applications, coarse spatiotemporal resolution satellite outputs are insufficient. In the late 1990s, satellites suitable for PA, like as IKONOS, were launched. IKONOS, which was launched in 1999, gathered imageries with a 4-m spatial resolution in visible and NIR bands with a five-day revisit duration [22]. IKONOS imagery has been used in PA for a variety of applications, including soil mapping, crop growth and yield prediction, fertiliser management, and ET estimate [33,41–43]. Later years saw the launch of a slew of nanosatellite constellations, which addressed other issues with satellite imagery's spatial, spectral, and temporal resolution [66]. Nanosatellite constellations are made up of a large number of small spacecraft with inexpensive and replaceable sensors [47].

Land use and land cover Concept and Definitions

A land is an important natural resource that plays a vital role in human development and existence through the provision of food and shelter. Hence, studying LULC contributes to improve an understanding regarding the sustainable use of land resources for natural resource management and good land utilization. To understand the LULC classification process it is important to be familiar with the terms land, land-use and land-cover:

Land: According to FAO (1995), "Land is a delineable area of the earth's terrestrial surface, encompassing all attributes of the biosphere immediately above or below the surface, including those of the near-surface climate, soil and terrain forms, surface hydrology (including shallow lakes, rivers, marshes, and swamps), near-surface sedimentary layers and associated groundwater reserve, plant and animal populations, human settlement pattern, and surface hydrology (including shallow lakes, rivers, marshes,

Land-use: "Land-use" refers to the ways in which humans utilize the earth's surface (Turner and Meyer, 1994). The FAO (1995) defines land-use as "human activities that are directly related to land, making use of its resources, or having an impact on them," and it might include "human activities that are directly related to land, making use of its resources, or having an impact on them."

LULC classification system

Land-cover and land-use are two ways of looking at the earth's surface that are linked by two fundamental questions: what is this (land-cover) and what is it for? (land-use). To answer these questions, think about what things should be examined and what observation units should be considered. In most cases, land-cover and land-use are intertwined. The classification method may assist in resolving any ambiguity between the two names. The assessment of LULC dynamics is required for land and natural resource management on a regular basis. Huge amounts of cartographic data are now available, but the majority of them are unusable since they are out of date and impossible to combine with other data sources. In the year 1993, With the goal of standardizing data collection and management, FAO and UNEP have taken steps toward developing an internationally approved reference base for LULC classification. This endeavor reflects a belief that this classification can be used at any scale and in every location around the world (FAO and UNEP, 1994; Herold et al., 2006).

Di Gregorio and Jansen (2005) studied and said There are two primary types of LULC classification: hierarchical and non-hierarchical. Hierarchical categorization is preferred because it provides more consistency and incorporates many levels of information, beginning with systematic broad level classifications that are subdivided into specific level of sub-classes. A priori and posteriori classification are two approaches to classification. A priori classification is based on the definition of classes prior to data collection, in which many diagnostic criteria are dealt with in advance of data collection. The posteriori strategy is based on class definition after clustering the field samples. The term "posteriori" refers to a classification that is made after the fact. There is no classification that has been internationally accepted till today because of the different perspectives of classification purposes, scale and processes (Di Gregorio and Jansen, 2005). The classifications have been used according to the purpose of the study.

Roy et al. (2010) has developed certain categorization system criteria to solve challenges such as class definition, numerous lands use on a single land parcel, and minimum representable area These criteria include a minimum level of LULC category interpretation accuracy of at least 85%, the classification should be applicable to a large area, aggregation of classes must be achievable, and the classification should be compatible with data from different times of remote sensing. He proposed a multilevel LULC classification system in which LULC data is available at many levels, such as I, II, III, and IV. The level I and level II classifications are appropriate for investigations conducted on a national, interstate, or state-by-state basis.

LULC classification methods

The classification techniques involve translation of pixel values of satellite imagery into meaningful information. There are huge numbers of classification methods available today to group pixel values into meaningful categories. The commonly known classification methods include automated method, manual method and hybrid approach.

Horning (2004) studied the automated method involves two basic classification methods i.e. There are two types of classification: supervised classification, which requires prior knowledge of all cover types to be classified, and unsupervised classification, which requires no prior knowledge of land cover types. In compared to human visual methods, the advantage of an automated approach is that the algorithm is applied consistently and swiftly throughout the entire image, and many more layers can be used for categorization.

Hansen et al. (1996) has studied about both the automated classification methods produce reliable results, however, for supervised classification, a wider range of algorithms is available. Decision trees, neural networks (Foody et al., 1997), fuzzy classification (Foody, 1998; Mannan et al., 1998), and mixture modelling are some of the algorithms used for supervised classification (van Der Meer, 1995). Progressive generalisation (Cihlar et al., 1998) and classification via augmentation and post-processing changes are examples of unsupervised classification (Lark, 1995).

Chouhan et al. (2015) studied to evaluate the wheat yield response to drip irrigation systems, as well as the ascribed water productivity and saving water indices, under semi-tropical clay loam soil conditions over the 2011-12 rabi seasons to investigate the effect Drip irrigated wheat had a 24.24 percent higher water productivity than border irrigated wheat, according to the data. The grain yield, on the other hand, decreased by 10.8%. This could be because the wheat plants were subjected to more water stress during their developing phases. Finally, excellent irrigation water management under drip irrigation is promising for improved water productivity and can be used as an alternate irrigation method, However, more research under similar field settings is required. Effects of drip irrigation on wheat crop water productivity and yield attributes When comparing drip irrigation to border irrigation, the results showed that drip irrigation saves roughly 28.42 percent more water.

Ambika et al. (2016) studied about However, there are no high-resolution irrigated area maps for India with a long history that may be utilised for water resource planning and management. High-resolution irrigated area maps for all agroecological zones in India are generated using 250 m normalised difference vegetation index (NDVI) data from the Moderate Resolution Imaging Spectroradiometer and 56 m land use/land cover data for the period 2000–2015. The irrigated area maps were examined and compared to the previously created irrigation maps using agricultural statistics data from ground surveys.

Sophia et al. (2017) studied Land Use/Land Cover Classification Accuracy Assessment. The Non-Parametric Rule was used to perform supervised classification in this study. Agriculture (65.0%), water bodies (4.0%), built-up areas (18.3%), mixed forest (5.2%), and barren/bare land (5.2%) were the top LULC categories (0.5 percent). The overall classification accuracy of the study was 81.7 percent, with a kappa coefficient (K) of 0.722.

Pun et al. (2017) The spatial distribution of irrigated and non-irrigated croplands is classified and mapped using surface energy balance fluxes and vegetation indices in this remote sensing study. The goal is to provide a classification scheme that may be used across a wide range of regional climates and seasonal precipitation patterns. The formulation and calibration of the strategy based on the wettest growing season provides the basis for climatic and inter-growing seasonal adaptation. Two indices derived from evapotranspiration fluxes and vegetation indices are used to contrast and identify irrigated and non-irrigated croplands using empirical distribution functions. Through adding another classifying layer that reclassifies misclassified croplands by the base index, the synergy of the two indices improves classification competency.

Zubair (2006) studied about the classification methods and discover that when the user is familiar with the area to be categorised, the manual method is effective. Visual indications such as texture, tone, shape, pattern, and relationship to other items are used in this strategy. It mostly relies on the human brain to recognise and relate visual elements to the ground. For visual feature identification, human analysis still outperforms machine accuracy. Manual interpretation has the disadvantage of being tedious and time-consuming in compared to automatic classification due to its subjective character.

Importance of remote sensing and GIS in LULC studies

Remote sensing and geographic information systems (GIS) can be used to map, monitor, and model LULC changes. Prior to the availability of satellite images, remote sensing was used to create maps for LULC research using aerial photography. The reflected response of items on the earth's surface is captured through remote sensing. LULC change patterns can be identified and quantified using repeated synoptic coverage with consistent acquisition (Lo and Choi, 2004). Remote sensing is appropriate for LULC investigations because of characteristics such as repeated synoptic coverage, low cost, higher accuracy, less arduous, and time efficient (Kachhwaha, 1986). Continuous monitoring and modelling of LULC change processes is now possible thanks to the advent of high spatial resolution satellite imagery and increasingly advanced image processing and GIS technology. Remote sensing and GIS, in combination with statistical approaches, play an important role in model building, parameterization, model application, and model validation, all of which are beneficial to LULC change research (Terry and Benjamin, 2012).

Patle et al. (2020) a studied and the Nahra nala watershed, which is a tributary of the Wainganga River and is located in the Balaghat district of Madhya Pradesh, India, was mapped using SENTINEL-2B satellite data with a precise spatial resolution for land use/land cover mapping. Water bodies, agricultural land, forest, habitation (built-up), and wasteland were recognised as five land use/land cover types in the study region. Forest is the most common LU/LC type in the study area, accounting for 83.79 percent of the watershed's total geographical area.

Chander et al. (2009) find that the availability of huge freely available satellite data in Landsat archive represents great wealth for identifying and monitoring changes in natural and anthropogenic environments. Numerous researches around the world have used remote sensing and GIS techniques in various fields including LULC change analysis.

Ganasri and Dwarakish (2015) studied By comparing three classification algorithms, parallelepiped algorithm, minimum distance to mean strategy, and maximum likelihood algorithm, LULC dynamics in the Harangi catchment of Karnataka state in India were studied using LISS-III data for the years 2007, 2010, and 2013. The study found significant changes in forest area, plantation, and wasteland, with a decrease in forest of 183.12 km2 to 131.02 km2, a decrease in fallow land of 68.89 km2 to 42.63 km2, a decrease in water body of 6.71 km2 to 3.82 km2, and increases in plantation, waterlogged area, and urban area of 56.07 km2 to 146.55 km2, 17.99 km2 to 23.81 km2, and 13.06 km.

Rawat and Kumar (2015) studied LULC changes in Uttarkhand's Hawalbagh lock in the district of Almora. They classified LULC cover classes into five categories using supervised classification using maximum likelihood technique: vegetation, agricultural, barren terrain, built-up, and water body. Using the change detection method, they discovered 3.51 percent and 3.55 percent increases in vegetation, as well as 1.52 percent, 5.46 percent, and 0.08 percent increases in agricultural, barren land, and water bodies

Tian et al. (2014) used high-resolution remote sensing datasets to examine historical changes in India from 1880 to 2010 by combining current remote sensing datasets from Resourcesat-1 with historical tabular archives to produce more trustworthy LULC datasets. During the study period, they discovered a considerable decrease in forests (from 89 million ha to 63 million ha) and an increase in agriculture (from 92 million ha to 140.1 million ha). The study showed that rate of urbanisation was slower during 1880–1940 but significantly increased after the 1950 due to rapid population increase and economic growth in the country.

Tsarouchi et al. (2014) quantified and predicted the LULC changes in India's Upper Ganges basin using 30 m multi-temporal Landsat imagery (Landsat 5 Thematic Mapper and Landsat 7 Enhanced Thematic Mapper Plus). Images were subjected to post-classification change analysis methods in order to quantify changes from 1984 to 2010, and a Markov chain was used to forecast future LULC changes in the basin. During the research period, the study found a growth in urban and agricultural land, as well as a loss of shrubland and barren land.

Thenkabail et al. (2005) generated Using MODIS data from 2001–2002 and cloud removal methods such as blue-band minimum reflectivity cutoff and visible-band minimum reflectivity threshold, 29 LULC classes with 6 unique irrigated area classes were discovered in the Ganges and Indus river basins. The study looked at a total of 33.08 million hectares of net irrigated land, with canals accounting for 26.6 percent and groundwater accounting for 73.4 percent. 29 LULC classes had accuracy ranging from 56 percent to 100 percent.

Roy et al. (2015) quantify Using multi-temporal satellite imagery, researchers examined LULC trends in India from 1985 to 2005 at decadal intervals and discovered a considerable increase in built-up areas and crops, as well as a decrease in fallow land, forest, and wasteland.

Tripathi and Issac (2016) investigated The Ramganga River Basin is a large river basin in India. Satellite images (from 1979 to 2009) and a toposheet map of the subject area (Ramganga Basin, Bareilly District) were used in this investigation. Different software was also used, such as ArcMap and Erdas Imagine. Over the last 30 years, the study area has seen considerable changes in land use and land cover, according to the findings (vegetation decreases and settlement increases).

Tiwari et al. (2017) investigates the Using remote sensing and GIS, create a land use cover map for the Banjar River basin in 2009 and 2013. ERDAS IMAGINE software was used for the supervised categorization. River, water body, waste land, habitation, forest, agriculture/other vegetation, open land/fallow land/barren land were the seven categories used to classify the photos from the study region. The results show that forest, water body, waste land, and open land/fallow land/barren have increased by 2.26 percent, 0.55 percent, 0.23 percent, and 0.48 percent over the last five years, while river, habitation, and agriculture/other vegetation have decreased by 0.26 percent, 0.04 percent, and 3.22 percent This study included an accuracy assessment to determine the quality of the land use/cover map, and overall accuracy was found to be 89.70 percent in 2009 and 91.91 percent in 2013.

Barakat et al. (2017) used ASTER (Advanced Spaceborne Based on the supervised classification technique and the normalised difference vegetation index, pictures from the Thermal Emission and Reflection Radiometer) and Sentinel-2A MSI were taken in 2001 and 2015, respectively, for assessing changes in the Eastern area of Béni-Mellal province

(NDVI). Changes in land use have resulted in an increase in forest area, according to the study.

Demissie et al. (2017) used In the Libokemkem District of South Gonder, Ethiopia, Landsat data from 1973 to 2015 were used to examine LULC changes and their causes. In 42 years, 60.1 percent of the land has changed in LULC, according to their research. LULC analysis has been employed in several Moroccan studies that have used various forms of remote sensing data.

Soni et al. (2019) estimated the rainfall-runoff relationship by using SCS-CN method of rainfed Rewa district. From 2008 to 2017, the daily rainfall pattern in the catchment region was analysed for a ten-year period. From 2008 to 2017, the calculated runoff in mm was 198.42, 61.38, 173.27, 415.84, 622.56, 583.84, 107.32, 219.71, 791.34, and 294.57 mm. Using the SCS-CN approach, the minimum runoff of 61.38 mm was seen in 2009, and the greatest runoff of 791.34 mm was reported in 2016.

Behera et al. (2012) used The CA-Markov model was used to predict the future LULC scenario in the Choudwar watershed of India using satellite-derived LULC data from 1972, 1990, 1999, and 2005. They discovered an increase in agriculture area and settlement (181.96 and 9.89 ha/year), as well as a decrease in forest, wetland, and marshy land (91.22, 27.56, and 39.52 ha/year), implying that agricultural expansion was primarily responsible for the decrease in forest, wetland, and marshy land in the watershed.

Brink and Eva (2009) examined the LULC changes in sub-Saharan Africa using high-resolution Landsat imagery from 1975 to 2000. The study has shown that agricultural and barren land area has increased by 57% and 15% respectively at the expense of natural vegetation that has diminished by 21% during the 25 year period.

De Espindola et al. (2012) studied the impact of agriculture expansion on deforestation with the help of Landsat-TM imagery and agriculture census data of 1996 and 2007. They identified the determinants of deforestation with the help of spatial regression model by using accessibility to markets, public policies, agrarian structure as well as the environment, as driving forces. The regression model's findings show that distance to highways and the number of established families both played a role in deforestation.

Zhang et al. (2010) analyzed Guangzhou Metropolis, the metropolis of Guangdong Province in southern China, undergoes LULC modifications. They used DOM (Digital Orth Photo Map) to calculate the LULC changes from 2003 to 2005 and discovered that farmland in the study area has rapidly diminished due to conversion to other cultivated lands, with conversions from farmland to garden, constructional land, and other agricultural land accounting for 163.11 km2, 3,783.24 km2, and 136.28 km2 respectively.

Wasige et al. (2013) studied Thematic historical map from 1901, Topo sheets (1:50,000) from 1974, and Landsat photos from 1985, 1995, and 2005 were used to study human-induced LULC changes in the Lake Victoria watershed. Between 1901 and 2010, they discovered a 60 percent rise in agriculture areas and a loss of forest area (from 7% to 2.6%), woods (from 51 percent to 6.9%), and savannas (from 35 percent to 19.6%).

Abuelaish and Olmedo (2016) explored Landsat pictures from 1972, 1982, 1990, 2002, and 2013 were used to create a LULC change scenario for 2023 in Gaza Strip on the

Mediterranean coast. They used Idrisi Selva to simulate the LULC scenario utilising three GIS models: GEOMOD, CA Markov, and Land Change Modeler. By 2023, the Gaza Strip's urban area will have grown by 212.3 km2 (58.83 percent).

Jansen and Gregorio (2004) studied LULC changes in Lebanon using existing LULC maps at scale 1:50,000, land cover datasets prepared by visual interpretation of 1987 SPOT and 1987 Landsat TM imagery, 1966 forest map at scale 1:200,000, re-afforestation maps at scale 1:100,000, actual irrigation maps at scale 1:10,000 of 1996–1997, and agricultural map of 1980 at scale 1:200,000 According to the findings, urban areas account for 1.8 percent of the total area, field crops and fallow land (irrigated and unirrigated) account for 15.3 percent, forest area accounts for 13.3 percent, water bodies account for 0.2 percent, trees and perennial crops account for 10.1 percent, grassland (unimproved land) accounts for 45.4 percent, and unproductive land accounts for 7.5 percent.

Zhang et al. (2009) monitored Landscape changes in the Three Gorges Reservoir Area (TGRA) in China were studied using Landsat TM/ MSS photos from 1978, 1988, 1995, 2000, and 2005, as well as vegetation cover analysis using MODIS/ Terra pictures from 2000 to 2006. The analysis reveals that major LULC changes occurred in the area during the construction of the Three Gorges Dam, along with ongoing economic and urban/rural growth. The results show that farmland, woodland, and grassland areas have been steadily decreasing over the last 30 years, whereas built-up and river areas have increased by 4.45 percent and 2.79 percent, respectively. In addition to the above studies, there are numerous studies conducted around the world where the importance of remote sensing and GIS can be seen.

Studies based on vegetation indices

Despite the fact that there are a high number of available products that can be used in land cover/land use mapping, most of the reviewed authors use NDVI time series. NDVI is used more frequently than other indices largely to continue the AVHRR heritage and to facilitate the comparison with other studies (Gitelson and Kaufman 1998).

Vegetation types can be characterized using their seasonal or phenological variations. Annual seasonal parameters of reflectance data and NDVI, and metrics such as minimum, maximum, and amplitude, have the potential to improve land cover separability (Townshend et al. 1991, DeFries et al. 1995, Ji and Peters 2007). The effectiveness of NDVI time series has been demonstrated in several studies on crop discrimination of North America, Europe, and Asia (Mingwei and Qingbo 2008).

Some authors extract the seasonal parameters by using more than one year of NDVI records to retain sufficient data after eliminating noise (Tottrup 2007). Other authors use partial time series, restricting the data to a particular time of interest; for example, the growing season (Bagan et al. 2005, Sivanpillai and Latchininsky 2007), or a snow-free period (Heiskanen and Kivinen 2008).

Even though the use of NDVI is preferred by most authors, the use of other indices has been increasing. One of the most popular indices is the EVI provided in the MOD13 product. EVI was developed to optimize the vegetation signal with improved sensitivity in high biomass regions and improved vegetation monitoring through a decoupling of the canopy background signal and a reduction in atmospheric influences (Huete et al. 2002). Several authors indicate that EVI is more sensitive to variations in green vegetation cover when compared with NDVI

(Justice et al. 1998, Ferreira et al. 2003, Xavier et al. 2006). NDVI exhibits scaling problems, asymptotic (saturated) signals over high biomass conditions, particularly strong with high canopy background brightness (Huete 1988). Xavier et al. (2006) observed that EVI is sensitive to variations in land use cover due to phenology and land management practices.

Other less commonly used vegetation indices are more suited to particular monitoring requirements. Gitelson et al. (2005) suggested the use of the Green Index (GI) defined as: GI Rnir/Rgreen (where Rnir is the near infrared band and Rgreen is the green band). In the green spectrum, absorption of light is high enough to provide high sensitivity of the GI to chlorophyll content but much lower than in the blue and red to avoid saturation (Gitelson et al. 2003). Ozdogan and Gutman (2008) proved that the (GI) has a better performance than NDVI and EVI in the subpixel monitoring of irrigated crops. This can be explained by the fact that irrigated crops with very little or no soil moisture stress exhibit larger chlorophyll content than nonirrigated crops with potential moisture stress.

Studies based on surface reflectance data

Carrao et al. (2008) used multi-date composite surface reflectance products. Although preliminary investigations showed that the variable view geometry of the composites caused adjacent pixels to have large radiometric differences for the same cover type, leading to classification errors (Cihlar 2000). To avoid these difficulties, Wessels et al. (2004), Chen and Rao (2009) and Shimabukuro et al. (2009) used single date near cloud free imagery to map regional land cover. Sedano et al. (2005) used five single date images, as only five cloud-free single-day images corresponding to different periods of the dry season were available for southern Africa in this study.

Utilizing more than one kind of MODIS data

Some researchers find it useful to incorporate different kinds of MODIS data. For example, in order to generate the land cover and land cover dynamics products (MOD12), Friedl et al. (2010) added to bands 17 the information provided by the EVI and the LST. To compute the EVI they used NBAR.

Using more than one kind of data often enhances the spectral separability of the desired classes. Westra and De Wulf (2007) used information from medium infrared, near infrared, and an index based on these two bands, called the Normalized Difference Water Index combined with NDVI and EVI (Gao 1996). This method demonstrated a better performance than using only one variable by itself.

Another approach is the combination of more than one kind of sensor data. Braswell et al. (2003) took advantage of the nearly coincident imaging of the Multiangle Imaging Spectroradiometer (MISR) and MODIS (using multiple shortwave infrared bands), and merged these sets of data to map sub-pixel land cover fractions in the Brazilian Amazon region. They obtained an apparent synergistic effect providing an increase of 20 and 30%, respectively, for the correlation value and the average accuracy of the derived maps.

Yang (2006) employed a data mining technique to evaluate the degree to which the accuracy of land cover classification can be increased using multi-spectral, multitemporal, and multi-angle remote sensing data in a study area in South central New Mexico, USA. Data used for this study included EOS MISR surface BRF and MODIS 16-day NDVI composites acquired from 2002 to 2003. Eight land cover types were classified using a decision tree algorithm with multiple classifications obtained to evaluate classification accuracy using different input data (MODIS data only, MISR data only, and MODIS plus MISR data). The largest increase in accuracy was observed for open oak woodland, coniferous woodland, and woody wetland using MISR and MODIS data, and for irrigated cropland and barren land using MISR data only.

Acerbi-Junior et al. (2006) performed the fusion between MODIS and Landsat images using the wavelet transform. Their results indicated that the fusion of MODIS and TM images using the Fourier space wavelet transform provided the best quality measures for the fused images. This methodology can be beneficial in areas where there are gaps in the data series. Classification results showed that the fused images could be used for their study area with an accuracy level comparable to the Landsat TM image.

Hansen et al. (2008) used MODIS derived forest cover products to calibrate Landsat data allowing a standard processing stream that increases the internal consistency of the regional-scale cover characterizations. They found a standard error of the global MODIS vegetation continuous fields product for sites tested of 11.5%, according to the authors this accuracy is sufficient for identifying the broad tree cover strata required to map forest cover and change within the Congo Basin. They concluded that the multi-resolution methodology is portable, but requires study areas where the moderate and high spatial resolution thematic classes are the same and few in number, and where the land cover classes are spatially homogenous at scales larger than several moderate resolution pixels.

Three dimensions of data

A few authors compare the respective contributions of the three dimensions of data (temporal, spectral, and angular). Carrao et al. (2008) found that spectral information is more useful in discriminating land cover classes than temporal information. They demonstrated that the multi-temporal factor (choosing multiple dates) has a significant effect when coupled with combinations of few spectral bands, but the temporal contribution disappeared as soon as the full spectral information (seven bands) is exploited. In contrast, even with a full year of MODIS data, the results are strengthened when continuing to use no less than three spectral bands.

Heiskanen and Kivinen (2008) demonstrated that multi-temporal and angular variables can increase the accuracy of the cover estimates and forest mapping. Their results also suggest that seasonality affects the model performance; the late-spring and early-summer data providing superior results compared to mid- and late summer data.

Incorporation of ancillary data

The spectral similarity of many land surface types presents a challenge in differentiating these classes by using only spectral information. This problem grows as the sensor resolution decreases. Many authors have tried to use other sources of information in order to improve the final accuracy of the maps. For instance, to separate vegetation types with a similar spectral response but located in different ecological zones, it is useful to take into account the ecological conditions. The most frequently used ancillary data are elevation because it is highly related to ecological factors and it is easily obtained. Slope can be readily derived from the elevation model, and temperature is another element used in analyses. Some authors chose to use a combination of these ancillary data instead of only one.

Miettinen et al. (2008) used elevation data as ancillary data to separate 12 classes in South-east Asia. Friedl et al. (2010) used a combination of MODIS products and maps of prior probabilities to create the MOD12 collection five including reflectance, LST, BRDF, and EVI. Garcıa-Mora and Mas (2010) used MODIS data along with an elevation model and a map of soils to map land cover in a highly diverse region of Mexico. The incorporation of these ancillary data provided only a small increase in accuracy which was attributed to the overlap of the distribution of various land cover types with respect to these variables. Zhang et al. (2008a, 2008b) used slope together with EVI to map land cover in Northern China. The overall accuracy obtained significantly exceeded the accuracy of the MOD12 product previously produced by NASA and USGS. Ozdogan and Gutman (2008) used an effective irrigation potential map derived from climate and radiation data to map irrigated areas from multi-date MODIS data.

Soil Moisture

Soil moisture has been estimated globally using remote sensing data obtained in numerous bands, including optical, thermal, and microwave [74, 75, 76]. The "triangle" or "trapezoid" or land surface temperature-vegetation index (LST-VI) method [77,78–80] has extensively exploited optical and thermal remote sensing data for soil moisture and ET calculations. The triangle or LST-VI technique is based on the physical link between vegetative cover qualities and land surface temperature (and hence soil moisture and latent heat fluxes). The interpretation of the pixel distribution in the LST-VI plot-space is used to estimate soil moisture in this method. The LST-VI space resembles a triangle or trapezoid when a significant number of pixels are present in a picture encompassing the whole range of soil moisture and vegetation density and when cloud, surface water, and other outliers are eliminated [78]. The dry edge (low soil moisture) is represented by one edge of the LST-VI triangle or trapezoid decreasing toward higher temperatures, while the wet edge (high soil moisture) is represented by the opposite side [81]. The LST-VI space takes on a triangular or trapezoidal shape due to LST's low sensitivity to soil moisture under dense vegetative conditions, as opposed to its great sensitivity to soil moisture under bare soil or sparse vegetation situations. After determining the upper and lower limit moisture content for wet and dry boundaries, soil moisture for remaining pixels can theoretically be approximated using interpolation techniques. For soil moisture estimate, the triangle method uses a basic parametrization approach and does not require auxiliary atmospheric or surface data [78,82]. However, in the triangle technique, a subjective identification of wet and dry borders can add large inaccuracies in soil moisture measurement, particularly over generally homogeneous land surfaces. A novel generation of triangle models for high spatial resolution mapping of soil moisture in PA applications has recently been created and tested [83,84]. The optical trapezoid model (OPTRAM) replaces the LST in the standard triangle model with short-wave-infrared transformed reflectance in one such technique (STR). Soil moisture in OPTRAM is determined using the interpretation of STR-VI space, similar to the classic triangle model [84]. Sadeghi et al. [20] used Sentinel-2 and Landsat-8 data to show that the OPTRAM model can estimate soil moisture accurately (0.04 cm3/cm3) in grassland and agriculture dominated watersheds in Arizona and Oklahoma, USA. Because the OPTRAM model does not require thermal remote sensing data, it can be used with a wider spectrum of data. Surface reflectance (STR), unlike LST, is a function of surface qualities and does not vary greatly with ambient atmospheric conditions, hence there is no need to parametrize or calibrate the model for each individual. Microwave remote sensing data has a higher potential for providing precise soil moisture estimations than data gathered in the visible, NIR, and SWIR bands [80]. Signals in the visible and near-infrared ranges have a lower penetrating ability than microwave signals, and are more susceptible to interference produced by atmospheric and cloud conditions [85]. For soil moisture measurement, microwave sensors evaluate dielectric characteristics of soil based on land surface emissivity or scattering. The advanced microwave scanning radiometer-earth observing system (AMSR-E), soil moisture and ocean salinity (SMOS), soil moisture active passive (SMAP), and Sentinel-1 [80] have all been launched with active and passive microwave sensors for soil moisture monitoring. When compared to passive microwave sensors, active microwave sensors have a better spatial resolution. Active sensors, on the other hand, are subject to measurement errors due to land surface roughness and vegetation cover or canopy [86]. Passive sensors, on the other hand, are more accurate and provide superior temporal resolution, but they have a coarser geographical resolution (e.g., 10s of kilometres) [79]. Typically, better resolution data is required for watershed and regional scale hydrologic and agricultural applications, particularly PA [87].

Nutrient Management

Fertilizer application must be timely and appropriate in order to maximise crop growth and yields while reducing environmental damage from nutrient losses to groundwater and surface water. During planting and subsequent stages of crop growth, a recommended rate of fertiliser is usually sprayed consistently. Due to changes in soils, management, terrain, weather, and hydrology, crop fertiliser requirements vary geographically and temporally (during and between seasons) [88,89]. Using standard instruments like chlorophyll metres to map such fluctuation in crop nutrient status/requirement for PA applications could be difficult. Several remote sensing-derived vegetation indices (e.g., NDVI, SAVI) have been demonstrated to be significantly linked with plant chlorophyll content, photosynthetic activity, and plant production. Understanding the geographical variability in crop nutrient status, which is critical for PA, can be aided by mapping these indices.

Several tractor-mounted remote sensors that can assess plant nutrient status for real-time administration of spatially varying fertiliser rates have recently become available. Commercially available hand-held and tractor-mounted remote sensors that use crop reflectance data to determine and apply spatially variable fertiliser rates in real-time include Green Seeker, Yara N-sensor, and Crop Circle [90].

Remote sensors are frequently installed forward of the spray boom in tractor-mounted systems. In these systems, nitrogen (N) application rates are calculated using vegetation indicators (e.g., NDVI), which are then sent to a nutrient applicator/spreader for real-time fertiliser application. The measured vegetation indices are converted into appropriate N-application rates using various algorithms. The N-application rates are estimated in general by comparing observed vegetation indices in the target field to a reference vegetation index measured in a well fertilised (N-rich) plot/strip that is indicative of the target field. Several fertiliser rate calculation algorithms have been devised and effectively used in these commercially accessible sensors to determine vegetation-indices based in-season N-requirements for many crops [91,92].

Despite the commercialization of proximal remote sensing-based variable rate N-management technology, farmer adoption remains low in many agricultural companies [93]. The lack of unambiguous proof of considerable economic benefits (crop yield and/or profitability), particularly in commercial farm settings (i.e., large fields), is a barrier to widespread implementation of these technologies [94]. Research is being undertaken with UAVs and other remote sensors for a variety of crops in different climatic locations to further develop these remote sensing based technologies and enhance their benefits. Maresma et al. [95] investigated the usefulness of multiple vegetation indicators and crop height in calculating in-season fertiliser treatment rates for corn produced in Spain using photos obtained by a UAV. Green Seeker and Crop Circle sensors reduced N fertiliser use and boosted N productivity for winter wheat cultivation in China, according to Cao et al. [96]. Overall, mapping based on remote sensing crop nutrient status in Pennsylvania can help boost crop nutrient use efficiency while maintaining/increasing crop yields and avoiding harmful off-site nutrient losses.

Crop Monitoring and Yield

Crop growth and production must be monitored in order to understand the crop's reaction to the environment and agronomic methods and to build successful fieldwork and/or remedy management programmes [97]. LAI and biomass are two important crop health and development indices [98]. Many crop growth and yield forecasting models employ LAI as an input [99]. In-situ LAI estimation methods (physical and optical) are labor-intensive and time-consuming, similar to destructive field approaches for biomass estimation. Furthermore, these approaches do not produce a map of crop growth and biomass spatial variability [100,101]. Remote sensing data on crop growth (e.g., LAI) and biomass can be used to gather useful information on site-specific properties (e.g., soils, topography), management (e.g., water, nutrient, and other inputs), and various biotic and abiotic stressors (e.g., diseases, weeds, water, and nutrient stress) [102]. Remote sensing data can also be used to map changes in tillage and residue management, as well as their effects on crop growth [103]. In several studies [104,105], hyperspectral images paired with various machine learning and classification algorithms were used to map tillage and crop residue in agricultural areas. Such information on crop conditions and tillage practises can help design site-specific management plans, which may include variable irrigation. LAI and biomass have been estimated using remote sensing data for a variety of crops, including row crops, orchards, and vine crops [106–108]. Typically, such research establish a regression or machine learning based approach to estimate LAI and/or biomass for a target field using a collection of reference data (e.g., measured LAI and accompanying vegetation indices). Yue et al. [101] estimated biomass (R2 = 0.74) in several irrigations and fertiliser treatment plots for winter wheat cultivated in China using multiple spectral indices in conjunction with observed plant height. For Kinnow mandarins produced in Pakistan, Ali et al. [269] employed red-edge position (REP) recovered from hyperspectral images to estimate LAI (R2 = 0.93) and chlorophyll content (R2 = 0.90). REP is the location of the red-NIR slope's primary inflection point, which is caused by significant chlorophyll absorption in the red spectrum and canopy scattering in the NIR region [108]. Due to interference from the bare soil surface, accurate LAI estimate from reflectance data may be challenging, especially during early crop growth phases. Modified vegetation indices corrected for soil and other interferences have been proposed and used to estimate LAI to address this constraint [109]. Red-edge based vegetation indexes have recently been demonstrated to be useful for calculating LAI in a variety of crops [110]. There are two methods for estimating crop yields using remotely sensed data.

To estimate crop yield and biomass, biophysical factors (e.g., LAI) derived from remotely sensed data are first used in a crop model. Second, statistical (e.g., regression) or empirical connections are established between crop parameters/indices derived from remote sensing (e.g., NDVI, LAI) and observed crop yield and biomass in a typical agricultural field. Agricultural yield could then be mapped at a target crop field using the generated regression model or empirical connection. Crop modelling is a data-intensive method that necessitates a huge quantity of data in the form of model input parameters, meteorological data, and yield and biomass data.

Maresma et al. [111] evaluated the association between maize yield and biomass and spectral indicators recorded at the V12 stage using a regression-based technique. They also discovered that for a variety of fertiliser application rates, the red-based indices NDVI and wide dynamic range vegetation index (WDRVI) showed the highest connection with grain yields, similar to prior studies. In comparison to a single snapshot during the season, spatial mapping of crop biophysical characteristics or indices at numerous times during the growing season is likely to provide a better estimate of crop biomass and yield [102].

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