A Review on Applications and Utility of Remote Sensing and Geographic Information Systems in Agriculture and Natural Resource Management.

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 fibers which are fundamental for human survival [Awokuse et al. 2015 and Gillespie et al. 2017]. 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). There are many mechanical changes over the past century, such as the Green Revolution, have changed the look of agriculture [Patel et al. 2013]. And 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 [Pingali et al. 2012]. 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% [Pingali et al. 2012 and Wik et al. 2008]. The demand for food and agricultural products will continue to grow by another 30% by 20 and more than 70% by 2045 [World Bank]. 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 (World Bank 2020).

Geographic Information System (GIS):

GIS is powerful set of tools for collecting, storing, and retrieving the data at will, transforming and displaying the spatial data for particular purpose. The ability of GIS to analyse and visualize agricultural environments and work flows has proved to be very beneficial to those involved in the farming industry. Balancing the inputs and outputs on a farm is fundamental to its success and profitability. Spatial data are commonly in the form of layers that may depict topography or environmental elements. Nowadays, GIS technology is becoming an essential tool for combining various map and satellite information sources in models that simulate the interactions of complex natural systems. GIS can be used to produce images, not just maps, but drawings, animations, and other cartographic products. From mobile GIS in the field to the scientific analysis of production data at the farm manager's office, GIS is playing an increasing role in agriculture production throughout the world by helping farmers increase production, reduce costs, and manage their land more efficiently. While natural inputs in farming cannot be controlled, they can be better understood and managed with GIS applications such as crop yield estimates, soil amendment analyses, and erosion identification and remediation. To simulate regional crop productivity, the spatial crop model is developed firstly in this study by integrating Geographical Information System (GIS) with Environmental Policy Integrated System with Coupling of AVHRR and VGT data. GIS provides ways to overlay different 'layers' of data: the ecological conditions, the actual physiognomy and human pressure indices. GIS is a layer based and thematic system which provides the flexibility to overlay and review the indices for various changes in the site. The technology is utilised to its fullest in the planning and managing.

Integrated applications of GIS and RS in Precision Farming:

GIS distinguishes itself from the other two technologies in that it enables data from diverse sources to be integrated, analyzed, and even modeled owing to its powerful analytical functionality. These functions, however, cannot be fully realized if the GIS database is incomplete, inaccurate, or obsolete. By their nature, the data contained in a GIS database are either spatial (e.g., administrative boundaries and boundaries of land-cover parcel) or thematic (e.g., types of land cover). Traditionally, spatial data and some thematic data associated with them are digitized from existing topographic or land-use maps. Nevertheless, these maps are secondary in nature. They may not show all desired features because of map generalization. Second, topographic or land-use maps may be obsolete due to rapid changes on the ground. These limitations can be overcome with the use of remote sensing and/or GPS. Aerial photographs and satellite images are original and are able to offer more current areal-based data than do topographic and thematic maps, while GPS is an efficient method of collecting data in a timely fashion.

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 [Boursianis et al. 2020, Delgado et al. 2019 and Jha et al. 2019], 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 [Delgado et al. 2019 and Jha et al. 2019]. 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 [Elijah et al. 2018]. 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 [Elijah et al. 2018]. Due to the high spatial/spectral/radiometric/temporal resolutions required for Precision Agriculture 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 [Koch et al. 2004].

"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 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) the Moderate Resolution Imaging Spectro radiometer (MODIS).

Importance of Precision Farming (PF): It is defined as the application of technologies and principles to manage spatial and temporal variability associated with all aspects of agricultural production Many technological developments occurred in the last decade that has improvised the concept of precision farming. The adaptability of PF relies on the integration and utilisation of modern days technologies such new advance farm technologies with the single system site specific technologies. The technology varies from high-speed connectivity of internet, farmer awareness. PF is an integrated, information and agricultural management system that is designed to improve the whole farm production efficiency with the low-cost effect while avoiding the unwanted effects of chemical loading to the environment. The focus under PF is to gather information regarding the soil and crop condition and capture the sequence on the soil and crop conditions at spatial level

Precision Agriculture Using Remote Sensing Systems

Remote sensing systems for PA can be divided into two categories: sensor platform and sensor type. In sensor platform we have 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. Ground-based platforms may be 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 [Kamilaris et al. 2017]. 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 [Santosh et al. 2014]. Hyperspectral images have a large number of infectious bands of narrow width (20 nm) separated by minor wavelength increments [Nowatzki, et al. 2020].

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 [Teke et al. 2013, Chang et al. 2020 and Nagasubramanian et al. 2019]. 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 [Teke et al. 2013, Chang et al. 2020, Nagasubramanian et al. 2019, Chlingaryan et al. 2018, Camino et al. 2018 and Zarco-Tejada et al. 2016]. 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) [Mohammed et al. 2019]. 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 [Mulla et al. 2013]. 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 [Khanal et al. 2017]. Microwaves can also penetrate clouds, which gives them an edge over other types of sensors that use visible and near-infrared wavelengths.

Application of Remote Sensing and GIS in Natural Resource Management and Agriculture

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 [Palazzi et al. 2019 and Pereira et al. 2017]. 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. During the 1930s and 1940s, aerial photography was used to map soils, land usage, and agricultural conditions in the United States [Nellis et al. 2009]. 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 [With et al. 2019 and Forkuor et al. 2017]. 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 [Still et al. 1985]. 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. A list some sensors used in PA can be seen in the 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 [Kidder et al. 1995]
AVHRR (1979–present)	MS (1.1 km)	1 day	Nutrient management

			[Leslie et al. 2017]
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 [Seelan et al. 2003]; crop yield [Scudiero et al. 2016]; crop growth [Venancio et al. 2019]
SPOT 1 (1986–1990) SPOT-2 (1990–2009)	MS (20 m)	2–6 days	Water management [Dong et al. 2016]
IRS 1A (1988–1996)	MS (72 m)	22 days	Water management, nutrient management [Worsley et al. 2001]
LiDAR (1995)	VIS (10 cm)	N/A	Topography, nutrient management [www.regional.org 2020]
RadarSAT (1995–2013)	C-band SAR (30 m)	1–6 days	Crop growth [Mondal et al. 2009]
IKONOS (1999–2015)	MS (3.2 m)	3 days	Crop yield [Koenig et al 2015]; soil properties [McNairn et al. 2002]; nutrient management [Leslie et al. 2017]; ET estimation [Enclona et al. 2004]
EO-1 Hyperion (2000–2017)	HS (30 m)	16 days	Disease [Sullivan et al. 2005, Yang et al. 2014]
Terra/Aqua MODIS (Terra-1999–present, Aqua-2002–present)	MS (Spectro Radiometer; 250–1000 m)	1–2 days	Crop yield [Omran et al. 2018]; crop growth [Apan et al. 2004]
Terra-ASTER (2000–present)	MS and Thermal (15 m–V, NIR, 30 m–SWIR, 90 m–TIR)	16 days	Water management [Filippi et al. 2019]
QuickBird (2001–2014)	MS (2.44 m)	1–3.5 days	Disease [Houborg et al . 2016]
AQUA AMSR-E (2002–2016)	MS (Microwave Radiometer; 5.4 km–56 km)	1–2 days	Water management [Mobasheri et al. 2007]
Spot-5 (2002–2015)	MS (V, NIR–10 m, SWIR–20 m)	2–3 days	Crop yield [Santoso et al. 2011]
ResourceSat-1 (2003–2013)	MS (5.6m–V, 23.5 m–SWIR)	5 days	Nutrient management [Jackson et al. 2003]
KOMPSAT-2 (2006–present)	MS (4 m)	5.5 days	Crop yield [Yang et al. 2009]
Radarsat-2	C-band SAR (1–100 m)	3 days	LAI and biomass [Sai et al. 2008]
RapidEye (2008–present)	MS (6.5 m)	1–5.5 days	Water management [Lee et al. 2011]; crop yield [Gao et al. 2013]; crop

			growth and chlorophyll [Siegfried et al. 2019]
GeoEye-1 (2008–present)	MS (1.65 m)	2.1–8.3 days	Nutrient management [De Lara et al. 2019]
WorldView-2 (2009–present)	MS (1.4 m)	1.1 days	Crop growth [Shang et al. 2015]
Pleiades-1A (2011–present) Pleiades-1B (2012–present)	MS (2 m)	1 day	Crop growth [Caturegli et al. 2015 and Tian et al. 2017]
VIIRS Suomi-NPP (2011–present) VIIRS-JPSS-1 (2017–present)	MS (IR Radiometer, 375 m and 750 m)	16 day (repeat)	Crop management (NDVI [Kokhan et al. 2020]
KOMPSAT-3 (2012–present)	MS (2.8 m)	1.4 days	Crop growth [Romanko et al. 2017]
Spot-6 (2012–present), Spot-7 (2014–present)	MS (6 m)	1-day	Disease [Skakun et al. 2018]
SkySat-1 (2013–present) SkySat-2 (2014–present)	MS (1 m)	sub-daily	Crop growth [Kim et al. 2006]
Worldview-3 (2014–present)	SS (1.24 m)	<1 day	Crop growth [Yuan et al. 2016]; weed management [De Lara et al. 2019]
Sentinel-1 (2014–present)	C-band SAR (5–40 m)	1–3 days	Crop growth [Kim et al. 2006]
Sentinel-2 (2015–present)	MS (10 m–V and NIR, 20 m–Red edge and SWIR, 60 m–2 NIR)	2–5 days	Yield [Yuan et al. 2016]; N management [Sidike et al. 2018]
KOMPSAT-3A (2015–present)	MS (V NIR–2.2 m, SWIR–5.5 m)	1.4 days	Disease [Martínez-Casasnovas et al. 2019]
SMAP (2015–present)	L-band SAR (1–3 km) and radiometer (40 km)	2–3 days	Crop yield [Wolters et al 2019]; water management [Bajwa et al. 2017]
TripleSat (2015–present)	MS (3.2 m)	1 day	Crop growth [El Sharif et al. 2015]
ECOSTRESS-PHyTIR (2018–present)	Thermal (38 $\times$ 69 m)	1–5 days	ET [Hao et al. 2019]

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 [Mohammed et al. 2019]. 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 [Leslie et al. 2017, Koenig et al. 2015, McNairn et al. 2002 and Enclona et al. 2004]. Later years saw the launch of a slew of nanosatellite constellations, which addressed other issues with satellite imagery's spatial, spectral, and temporal resolution [Yuan et al. 2016]. Nanosatellite constellations are made up of a large number of small spacecraft with inexpensive and replaceable sensors [Apan et al. 2004].

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. 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 (Herold et al. 2006).

Di Gregorio and Jansen (2005) studied and classified into 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 types of LULC 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; and mixture modelling are some of the algorithms used for supervised classification. Progressive generalisation (Cihlar et al. 1998) and classification via augmentation and post-processing changes are examples of unsupervised classification.

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.

Retto (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. Remote sensing is appropriate for LULC investigations because of characteristics such as repeated synoptic coverage, low cost, higher accuracy, less arduous, and time efficient. 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.

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.

Soil Moisture

Soil moisture has been estimated globally using remote sensing data obtained in numerous bands, including optical, thermal, and microwave [Chua et al. 2020, Fisher et al. 2020 and Zhou et al. 2016]. The "triangle" or "trapezoid" or land surface temperature-vegetation index (LST-VI) method [Verstraeten,et al. 2008, Zhang et al. 2016 and Carlson et al. 2007] 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 [Zhang et al. 2016]. 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 [Zhu et al. 2017]. 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 [Zhang et al. 2016 and Babaeian et al. 2019]. 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 [Petropoulos et al. 2009 and Carlson et al. 2019]. 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 [Carlson et al. 2019]. Sadeghi et al. 2020 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 [Carlson et al. 2007]. 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 [Babaeian et al. 2019]. 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 [Carlson et al. 2007] 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 [Sadeghi et al. 2017]. 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) [Zhang et al. 2019]. Typically, better resolution data is required for watershed and regional scale hydrologic and agricultural applications, particularly PA [Chen et al. 2019].

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) [Wagner et al. 2007 and Mohanty et al. 2017]. 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 [Hendricks et al. 2019].

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 [Melkonian et al. 2008 and Ali et al. 2017].

Despite the commercialization of proximal remote sensing-based variable rate N-management technology, farmer adoption remains low in many agricultural companies [Franzen et al. 2016]. 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 [Scharf et al. 2011]. 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. 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 [Colaco et al. 2018]. 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 [Marino et al. 2015]. LAI and biomass are two important crop health and development indices [Cao et al. 2017]. Many crop growth and yield forecasting models employ LAI as an input [Peng et al. 2019]. 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 [Zhou et al. 2016 and Kross et al. 2015]. 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) [Kang et al. 2016]. Remote sensing data can also be used to map changes in tillage and residue management, as well as their effects on crop growth [Yue et al. 2017]. In several studies [Campos et al. 2019 and Yeom et al. 2019], hyper-spectral 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 [Salas et al. 2019, Hively et al. 2018 and Jin et al. 2015]. 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. 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 2020 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 [Jin et al. 2015]. 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 [Kalisperakis et al. 2015]. Red-edge based vegetation indexes have recently been demonstrated to be useful for calculating LAI in a variety of crops [Ali et al. 2020]. 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. (2016) 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 [Kang et al. 2016].

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