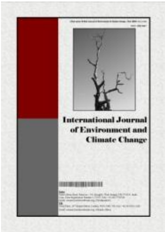

International Journal of Environment and Climate Change

12(4): 1-18, 2022; Article no.IJECC.81195
ISSN: 2581-8627
(Past name: British Journal of Environment & Climate Change, Past ISSN: 2231–4784)

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

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Authors' contributions

This work was carried out in collaboration among all authors. All authors read and approved the final manuscript.

Article Information

DOI: 10.9734/IJECC/2022/v12i430651

Open Peer Review History:
This journal follows the Advanced Open Peer Review policy. Identity of the Reviewers, Editor(s) and additional Reviewers, peer review comments, different versions of the manuscript, comments of the editors, etc are available here: https://www.sdiarticle5.com/review-history/81195

Review Article

Received 15 November 2021
Accepted 20 January 2022
Published 26 February 2022

ABSTRACT

Emerging technologies include remote sensing, global positioning systems (GPS), geographic information systems (GIS), and the Internet of Things. The Internet of Things (IoT), Big Data analysis, and artificial intelligence (AI) are all the promising tools that are being used to solve complications, improve agricultural operations, and reduce expenses. Satellite remote sensing has been indispensable in understanding Earth and atmospheric dynamics over the last five decades. When compared to ground or aerial sensor acquisitions, satellite sensors have the ability to provide data at global sizes at a lower cost. With the support of satellite remote sensing, the scientific community has attained significant progress in recent years. In consideration of these efforts, the current study is intended to provide a comprehensive review of the function of remote sensing in assessing different water security challenges and other purposes. Crop production forecasting, drought assessment, cropping system analysis, horticultural assessment and development, crop development, thorough site analysis, satellite agro-meteorology, precision farming, crop insurance, and other operational big agricultural applications are examples. This research examines various uses as well as potential gaps in the market.

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Keywords: Remote sensing; geographic information systems; satellite sensors and precision farming.

1. INTRODUCTION

Agriculture supplies nutritious food that are important for survival in both underdeveloped and developed countries [1,2]. "The world's population is predicted to double by 2050," according to the World Summit on Food Security. In comparing to 2013, growing economies will increase agriculture demand by almost 50% [3]. Many technological advances, such as the Green Revolution, have changed the face of agriculture over the last century [4]. During the 1960s–1980s, the third agricultural revolution, known as the Green Revolution, was defined by high yield crop types, the use of synthetic fertilisers, pesticides, and a water system [5]. increased seed yield and nutritional security, particularly in underdeveloped nations. As a result, despite the fact that the global population has doubled and consumption pattern has tripled since the 1960s, agriculture has only been able to meet demand by growing its cultivated area by 30% [5,6]. According to the World Bank, demand for food and agricultural goods would increase by another 30% by 2025 and by more than 70% by 2045. Because arable land is limited, agricultural intensification, which will increase fertiliser, insecticide, water, and other inputs, will meet a large portion of this growth in demand. Agriculture is undergoing its fourth revolution, which is being supported in great part by advances in information and communication technologies [8].

2. GEOGRAPHIC INFORMATION SYSTEM (GIS)

GIS is a set of strong tools for obtaining, storing, and retrieving data on demand, as well as changing and displaying spatial data for specific purposes. GIS's capacity to analyse and display agricultural settings and work flows has proven to be quite beneficial for individuals in the farming business. On a farm, balancing inputs and outputs is critical to its success and profitability. Layers depicting topography or environmental factors are widely used to represent spatial data. GIS technology is increasingly has been used in models that replicate the interactions of complex natural systems by integrating diverse map and satellite information sources. GIS can be used to create a picture, such as drawings, animations, and other cartographic products, in addition to maps. GIS is playing an increasingly important role in agriculture production around the world, helping farmers boost production, cut costs, and manage their land more efficiently, from mobile GIS in the field to scientific analysis of production data at the farm manager's office. While natural inputs in agriculture cannot be controlled, GIS applications such as crop yield projections, soil amendment assessments, and erosion detection and remediation can help farmers better understand and manage them. The spatial crop model is first established in this study by combining Geographical Information System (GIS) with Environmental Policy Integrated System with Coupling of AVHRR and VGT data to simulate regional crop productivity. GIS allows you to overlay many 'layers' of data, such as environmental conditions, the doctor's office, and so on. Human pressure indices and actual physiognomy GIS is a thematic and layer-based method that enables you to overlay and review indices for various changes in the site. In the development and preparation, technology is used to its highest potential.

3. INTEGRATED APPLICATIONS OF GIS AND RS IN PRECISION FARMING

To its robust analytical functionality, GIS stands out from the other two technologies in that it maintain confidence from many sources to be merged, analysed, and even modelled. However, if the GIS database is inadequate, erroneous, or old, these features will not be fully realised. The data in a GIS database is either geographical (e.g., administrative boundaries and land-cover parcel boundaries) or thematic (e.g., land-cover parcel boundaries) (e.g., types of land cover). Traditionally, topographic or land-use maps have been digitised to create spatial data and some thematic data. These maps, however, are secondary in character due to map generality, they may not show all desired features. Second, due to quick changes on the ground, topographic and land-use maps may become obsolete. Remote sensing and/or GPS can be used to overcome these constraints. Aerial pictures and satellite images are unique and can provide more current area-based data than topographic and thematic maps, while GPS is a quick and efficient way to obtain data. A few examples of developing technology are remote sensing, global positioning systems (GPS), geographic information systems (GIS), and the Internet of Things. The Internet of Things (IoT), Big Data analysis, and artificial intelligence (AI) are all the promising techniques that are being used to solve various problems, improve agricultural operations and inputs with the goal of increasing output while lowering costs [8-10], and yield losses [8-10] In many IoT technology solutions, cloud computing and wireless sensors are used. Automated wireless-controlled irrigation systems and intelligent farming are examples of smart farming operations. Delgado et al. [9] and Jha et al. [10] created disease and pest monitoring and forecasting systems using networks and big data analysis. AI techniques like as machine learning (e.g., artificial neural network have been used to estimate ET, soil moisture, and crop projections for automated and precise application of water, fertiliser, herbicides, and insecticides [11]. Farmers can utilise these technologies and methods to assess geographic diversity (e.g., soils) among farms and large crop fields, which can affect crop development and yields [11]. Remote sensing systems that use information and communication technologies generally generate a large volume of spectrum data due to the high spatial/spectral/radiometric/temporal resolutions necessary for Precision Agriculture applications. Emerging data processing techniques such as Big Data analysis, artificial intelligence, and machine learning have been utilised to extract useful information from the large amount of data [12].

According to the World Summit on Food Security, "the world's population is expected to grow to almost 10 billion by 2050, expanding agricultural demand by around 50% under a scenario of modest economic growth," compared to 2013 [3]. Any increase in food production, however, must be accompanied by a long-term agricultural land management strategy to avoid or at the very least ameliorate negative impacts on water and soil quality and quantity, land degradation, greenhouse gas emissions, and biodiversity [13]. Agriculture monitoring through using remote sensing is a huge field that has been extensively used for multiple outlooks, occasionally based on specific presentations (like, precision farming, prediction of yield, irrigation, weed identification), several remote sensing platforms (e.g. satellites, Unmanned Aerial Vehicles as UAVs, Unmanned Ground Vehicles – UGVs), sensors, and other factors or passive sensing, wavelength domain, geographical sampling), or specific geographic and climatic conditions. The growing body of published research suggests that remote sensing for agriculture has reached a point of maturity, and that interest in agricultural applications is growing at an exponential rate, especially since 2013. This growing works also reflects significant advances in relevant technology, such as sensing devices with unprecedented spatial, temporal, and spectral capacities (e.g. Sentinels, Gaofen), the introduction of small new platforms like nano-satellites or unmanned aerial vehicles (UAV), the use of cloud computing and several machine learning techniques. Remote sensing in agriculture should be able to attain long-term goals as a result of these innovations. Consistent observations of the terrestrial environment are crucial for understanding climate change and its effects, sustaining economic development, effectively managing natural resources, encouraging conservation, preserving biodiversity, and advancing scientific understanding of ecosystems. Since the late 1980s, there has been an increased emphasis on the usage of coarse resolution optical data, mainly the National Oceanic and Atmospheric Administration's Advanced Very High Resolution Radiometer (AVHRR) images (NOAA). For the sake of all land The AVHRR was initially accessible at an 8 km resolution and advanced at a notional resolution of 1 km in some parts of the planet. Data has become increasingly affordable (especially for research reasons), and some data is now available for free via direct broadcast. New satellite sensors, such as the SPOT 4 VEGETATION (VGT) Moderate Resolution Imaging Spectro radiometer, have been launched (MODIS).

Precision farming (PF) is described as the use of technologies and principles to achieve spatial and temporal variability in all elements of agricultural production. In the recent decade, many technical advancements have improved the concept of precision farming. PF's adaptability is based on the integration and use of modern technologies such as advanced farm technologies and single system site specific technologies. High-speed internet connectivity and farmer awareness are examples of technology. PF is an integrated information and agricultural management system that is aimed to increase overall farm production efficiency at a cheap cost while avoiding the negative environmental consequences of chemical loading. The goal of PF is to collect information about soil and crop conditions and to capture the sequence of those conditions at a spatial level.

4. PRECISION AGRICULTURE USING REMOTE SENSING SYSTEMS

There are two types of remote sensing systems for PA: sensor platform and sensor type.

Satellites, aerial platforms, along with ground-based platforms are popular areas for sensors to be put in sensor platforms. Since the 1970s, satellite technology has been regularly used for PA. In Pennsylvania, aircraft and unmanned aerial vehicles (UAVs) have been recently been used. The three types of ground-based platforms utilised for PA are hand-held, free-standing in the field, and mounted to a tractor or farm equipment. Ground-based systems are also known as proximal remote sensing systems since they are located close to the target surface in comparison to aerial or satellite-based platforms (land surface or plant). The geographical, spectral, radiometric, and temporal resolution of sensors employed for remote sensing differs [14]. Sensors used for remote sensing have different spatial, spectral, radiometric, and temporal resolutions [14]. The spatial resolution of a sensor is defined by the size of the pixel that shows the region on the ground. Sensors with a small footprint have a high spatial resolution, while those with a wide footprint have a low spatial resolution. Rather than the sensor itself, the sensor platform can be viewed of as having a high temporal resolution. Temporal resolution, for example, is the time it takes a satellite to complete an orbit and return to the same observation location. The spectral resolution of a sensor is determined by the number of bands captured in a particular span of electromagnetic spectrum [15]. Hyperspectral photographs width (20 nm) separated by minor wavelength increments [16].

A variety of vegetation indices, statistics, and machine learning algorithms, such as deep convolutional neural network and random forest, have been used to reduce the dimensionality of hyperspectral data and extract meaningful information on crop conditions [17,18,19]. Hyperspectral image quantification of solar-induced chlorophyll fluorescence (SIF) has recently been used to quantify photosynthesis, plant nutrients, and biotic and abiotic stressors like disease and water stress [17-22]. The suitable spatio-temporal determination necessary for PA is determined by various aspects, including management objectives, field size, and the flexibility of farm equipment to change input application rates (irrigation, fertiliser, pesticide, etc.). Crop biomass and yield estimation frequently require higher spatial resolution (1–3 m) than variable rate fertiliser and irrigation (5–10 m) applications [23]. Satellites, planes, and unmanned aerial vehicles (UAVs) all include sensors that are passive, meaning they don't have their own light source. Active sensors are onboard some spacecraft, such as the ERS-1/2's active microwave instrument (AMI). Many ground-based remote sensing systems use active proximity sensors. In commercially available variable fertiliser rate application systems like Green Seeker and Crop Circle, active proximity sensors are used.

In such systems, daylight variations had the least effect on measured reflectance, resulting in more precise and repeatable normalised difference vegetation index (NDVI) or further vegetation indices (VI) for crop nutritional grade monitoring. Other instruments (thermal infrared and microwave) deployed on later satellites are increasingly being employed in agriculture. Thermal infrared sensors measure the amount of energy emitted by a target (such crops) to determine its temperature, which can subsequently be used to compute crop water stress, ET, and irrigation requirements [24]. Microwave sensors, like thermal sensors, monitor the emitted energy (although in longer microwave wavelengths) from the ground surface [25]. Microwave sensors are mostly used to determine soil moisture content and crop water use over large areas. Microwaves can pass through clouds, giving them an advantage over sensors that employ visible and near-infrared wavelengths.

5. APPLICATION OF REMOTE SENSING, GIS IN NATURAL RESOURCE MANAGEMENT AND AGRICULTURE

For long-term natural resource management at the local, regional, and national levels, researchers have long recognised the need for mapping soil and land use records [26 and 27]. Irrigation, drainage, fertiliser, and additional crop management practises, which are essential components of PA, necessitate an understanding of soil physical, biological, and the chemical characteristics. Land use mapping can also be used to investigate the regional and national implications of present management and policy. A traditional method of using remote sensing techniques in agriculture existed even before the term "remote sensing" was coined in 1958. Aerial photography was employed to map soils, land use, and agricultural conditions in the United States during the 1930s and 1940s [28]. Traditional soil mapping and land use classification methods (such as low altitude photography and ground crews) frequently need extensive fieldwork and laboratory analysis, which is both expensive and time-consuming [29 and 30]. Satellite remote sensing was introduced later, enabling for more efficient and effective mapping of land use and land cover at regional, national, and global scales. Vanguard 2 and TIROS 1 were the first meteorological satellites to be launched, in 1959 and 1960, respectively [31] yield Landsat 1 (formerly known as the Earth Resources Technology Satellite-ERTS) was launched by the National Aeronautics and Space Administration on July 23, 1972, ushering in a new era of satellite remote sensing for agriculture (NASA). NASA and the US Geological Survey of the US Department of the Interior jointly oversee the Landsat programme (USGS). Following Landsat 1, a series of Landsat satellites (Landsat 2–8) were propelled to provide high-quality photos to researchers, land managers, and policymakers to aid in the global management of natural resources.

Satellite data from these flights was used to classify land use and crops in many major portions of the world. Satellite products were also used to track soil and vegetation health, as well as hydrologic and meteorological parameters that are most important for PA (like, soil organic carbon content, moisture of soil, NDVI and LAI), groundwater and rainfall amount. When compared to aerial photography, which was previously used to classify land use across large areas, satellite photographs proved to be more cost-effective. However, coarse spatiotemporal resolution satellite outputs are insufficient for many PA applications. Satellites appropriate for PA, such as IKONOS, were launched in the late 1990s [23]. IKONOS, which was inaugurated in 1999, captured imaginings with a 4-m spatial resolution under visible and NIR bands over a five-day return period. In Pennsylvania, IKONOS imagery has been utilised for soil mapping, crop growth, development and yield estimation, fertiliser detrmination, and ET estimation [33,41,42,43]. In recent years, a flurry of nanosatellite constellations have been launched, addressing various concerns 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].

6. LAND USE AND LAND COVER CONCEPT AND DEFINITIONS

The land is a valuable natural resource that highly contributes to human progress along with existence by providing food and shelter. As a result, studying LULC adds to a better knowledge of the long-term use of land resources for natural resource management and efficient land use. It is necessary to be familiar with the terms land, land-use, and land-cover in order to comprehend the LULC classification process.

"Land" is defined as "a definable area of the earth's terrestrial surface, covering all aspects of the biosphere directly above or below the surface, counting those of the near-surface climate, soil and terrain practises, surface hydrology (together with shallow lakes, rivers, marshes, and various swamps), near-surface sedimentary layers and related groundwater spare, plant and animal inhabitants, human settlement arrangements, and hydrology of surface," according to FAO [73]. (Including shallow lakes, rivers, and marshes).

Land-use: The manner in which humans utilise the earth's surface are referred to as "land-use." Land-use is well-defined by the FAO [73] as "human activities directly related to land, making use of its resources, or having an impact on them," and it may include "human activities directly related to land, making use of its resources, or having an impact on them."

7. LULC CLASSIFICATION SYSTEM

Land-cover area and land-use are two perspectives on the earth's surface related by two basic questions: what is the means of this (land-cover) and how it is for? (land-use). Consider what should be examined and what observation units should be considered when answering these questions. The lot of the sample, land cover and land use are interwoven. The classification technique can help to clear up any confusion between the two names. The examination of LULC dynamics is necessary on a regular basis for land and natural resource management. Enormous quantities of cartographic statistics are now available, but the mostly of them are useless since they are outdated and difficult to connect with other data sources. FAO and UNEP took initiatives toward building an internationally acknowledged reference base for LULC categorization in 1993, with the goal of standardising data collection and administration. This project expresses the concept that this classification can be applied at any scale and in every region on the planet [74].

Table 1. Shows a list of some of the sensors utilised in PA

Satellite (Years Active)	Spatial Sensors Resolution	Sequential Resolution	Utilization in Precision Agriculture
Landsat-1 (1972–1978)	MS (80 m)	18 days	In crop growth [32]
AVHRR (1979–present)	MS (1.1 km)	1 day	Management of nutrients [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 assessment [34]; crop yield [35]; crop growth [36]
SPOT 1 (1986–1990) SPOT-2 (1990–2009)	MS (20 m)	2–6 days	Water of management [37]
IRS 1A (1988–1996)	MS (72 m)	22 days	Water of management, nutrients management [38]
LiDAR (1995)	VIS (10 cm)	N/A	Geography, nutrient management [39]
Radar SAT (1995–2013)	C-band SAR (30 m)	1–6 days	Crop advancement [40]
IKONOS (1999–2015)	MS (3.2 m)	3 days	Yield of crop [41]; soil properties [42]; nutrient management [33]; ET estimation [43]
EO-1 Hyperion (2000–2017)	HS (30 m)	16 days	Disease screening [44, 45]
Terra/Aqua MODIS (Terra-1999–present, Aqua-2002–present)	MS (Spectro Radiometer; 250–1000 m)	1–2 days	Plant 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 of management [48]
QuickBird (2001–2014)	MS (2.44 m)	1–3.5 days	Disease identification [49]
AQUA AMSR-E (2002–2016)	MS (Microwave Radiometer; 5.4 km–56 km)	1–2 days	Water of management [50]
Spot-5 (2002–2015)	MS (V, NIR–10 m, SWIR–20 m)	2–3 days	Crop growth [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	Seed yield [53]
Radarsat-2	C-band SAR (1–100 m)	3 days	LAI and biomass accumulation [54]
Rapid Eye (2008–present)	MS (6.5 m)	1–5.5 days	Water supervision [55]; crop yield [56]; crop growth and chlorophyll [57]
GeoEye-1 (2008–present)	MS (1.65 m)	2.1–8.3 days	Nutrient monitoring [58]

Satellite (Years Active)	Spatial Sensors Resolution	Sequential Resolution	Utilization in Precision Agriculture
WorldView-2 (2009–present)	MS (1.4 m)	1.1 days	Crop development [59]
Pleiades-1A (2011–present) Pleiades-1B (2012–present)	MS (2 m)	1 day	Crop evolution [60 and 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 development [63]
Spot-6 (2012–present), Spot-7 (2014–present)	MS (6 m)	1-day	Disease indication [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 advancement [66]; weed management [58]
Sentinel-1 (2014–present)	C-band SAR (5–40 m)	1–3 days	Crop growing [65]
Sentinel-2 (2015–present)	MS (10 m–V and NIR, 20 m–Red edge and SWIR, 60 m–2 NIR)	2–5 days	Yield of plants [66]; N management [67]
KOMPSAT-3A (2015–present)	MS (V NIR–2.2 m, SWIR–5.5 m)	1.4 days	Disease [68]
SMAP (2015–present)	L-band SAR (1–3 km) and radiometer (40 km)	2–3 days	Crop yield [69]; water management [70]
TripleSat (2015–present)	MS (3.2 m)	1 day	Crop progress [71]
ECOSTRESS-PHyTIR (2018–present)	Thermal (38 $\times$ 69 m)	1–5 days	ET [72]

Di Gregorio and Jansen [75] 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 dissimilar perspectives of arrangement purposes, scale and procedures [75]. The types of LULC classifications have been used according to the purpose of the study.

Roy et al. [76] has developed certain categorization system criteria to solve challenges such as class definition, numerous lands use on a particular land parcel, and least represent able regions. These standards involve a minimum level of LULC category explanation correctness of at least 85%, the cataloguing must be appropriate for a large area, combination of different classes must be attainable and the classification might be compatible along-with data at various times of remote sensing. He projected a multilevel LULC arrangement system in which LULC data is presented at many stages, such as I, II, III, and IV. The level I and level II classifications are appropriate in investigations conducted on a national, interstate, or state-by-state basis.

8. 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 [77] studied the automated method involves two basic classification methods i.e. There are two types of classification: supervised grouping, which needs prior information related with all cover types to be classified, and unsupervised arrangement, that requires no prior facts related to land cover styles. In compared with human pictorial methods, the advantage of an automatic approach is that the algorithm is practically steadily and quickly throughout the entire image, and several other layers can be used for classification.

Hansen et al. [78] has studied about both the mechanical classification methods depicting more reliable results, however, for supervised ordering, is a wider range of algorithms is available. Trees, neural networks [79], fuzzy classification [80], and combination modelling are a few algorithms used for supervised classification. Progressive generalisation [81] and cataloguing by augmentation and post-processing changes are examples of unsupervised classification.

Chouhan et al. [82] studied to evaluate the response of wheat yield for drip irrigation arrangements, as well as ascribed water efficiency, saving indices of water, under semi-tropical clay - loam conditions of the soil 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 crop were subjected towards more water stress throughout their developing phases. Lastly, excellent irrigation water management in drip irrigation is capable system for improved water efficiency and might be used as an alternate irrigation method, However, more research under similar field settings is required. Effects of drip irrigation on wheat crop water output and yield characteristics When comparing drip irrigation to border irrigation, the results showed that drip irrigation saves roughly 28.42 percent more water.

Ambika et al. [83] studied about that there were no high-resolution irrigated region maps for India along-with large history that might be utilised for planning of water resources and super vision. High-resolution maps for all agro meteorological regions in India are generated using 250 m normalised difference vegetation index (NDVI) figures from the Moderate Resolution Imaging Spector-radiometer and 56 m land use and/or land cover records for the period 2000–2015. This irrigated area maps are examined and compared to the previously created irrigation maps using agricultural figures collecting from differnt ground surveys.

Retto [84] studied Land Use/Land Cover Classification Accuracy Assessment. The Non-Parametric Rule were utilized to perform supervised grouping in this study. Agriculture (65.0%), water bodies (4.0%), built-up extents (18.3%), mixed forest area (5.2%), and unfertilised land (5.2%) are the top LULC categories (0.5 percent). The inclusive classification accurateness of the research was noted 81.7 percent, along-with a kappa coefficient (K) of 0.722.

Pun et al. [85] the spatial circulation of irrigated as well as non-irrigated crop areas is classified and mapped using surface energy equilibrium fluxes and vegetation indices in this remote sensing study. The goal is to provide a classification scheme that may be used over a wide-ranging of regional climates and seasonal precipitation patterns. The formulation and standardisation of the strategy mainly based on the rainiest growing period provides basis for climatic and inter-growing seasonal adaptation. Two indices derivative from evapotranspiration fluxes and vegetation indices are used to difference and identify irrigated and non-irrigated crop regions using empirical distribution functions. Through adding other categorising layers that reclassifies misclassified crop regions by the base index, the synergy of the two indices improves ordering competency.

Zubair [86] 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.

9. IMPORTANCE OF REMOTE SENSING AND GIS IN LULC STUDIES

Remote sensing along with geographic information systems (GIS) can be used to map, monitor, and model LULC changes. Prior to the availability of several 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 due to the very high spatial resolution satellite imagery and increasingly progressive image processing and GIS technology. Remote sensing (RS) 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. [87] a studied the Nahra nala watershed area, which is a branch of the Wainganga River and is located in the Madhya Pradesh, Balaghat district, India, was mapped with SENTINEL-2B satellite figures along-with a precise spatial resolution for land use/land cover mapping. Water bodies, agricultural land, forest area, habitation, and wasteland reions were recognised as five land use/land cover types under the study district. Forest is the most common LU/LC type in the study area, accounting for 83.79% of the watershed's total geographical area.

10. SOIL MOISTURE

Remote sensing data gathered in a variety of bands, involving optical, thermal, and microwave, has been used to estimate soil moisture globally [88, 89, 90]. For soil moisture and ET calculations, the "triangle" or "trapezoid" or land surface temperature-vegetation index (LST-VI) technique [91, 92, and 93] has widely used optical and thermal remote sensing statistics. The triangle method, also known as LST-VI, is based on the physical relationship between vegetative cover quality and land surface temperature. In this method, the pixel distribution in the LST-VI plot-space is interpreted to determine soil moisture. When a large number of pixels are present in an image containing the entire range of soil moisture and vegetation density, and cloud, surface water, and other outliers are removed, the LST-VI space resembles a triangle or trapezoid [92]. One edge of the LST-VI triangle or trapezoid decreases to increasing temperatures, representing the dry edge (low soil moisture), whereas the opposite side represents the wet edge (high soil moisture)

[94]. Due of LST's low sensitivity to soil, the LST-VI space takes on a triangular or trapezoidal shape. Moisture in dense vegetative settings, vs its high compassion to soil moisture in bare soil or sparse vegetation situations. Soil moisture for remaining pixels can theoretically be calculated by interpolation practices after finding the upper and lower limit moisture content for wet and dry boundaries. The triangle method [92 and 95] uses a basic parametrization methodology to predict soil moisture and does not require supplemental air or surface data. However, a subjective determination of wet and dry borders in the triangle technique might introduce considerable mistakes in soil moisture assessment, especially over generally homogeneous land surfaces. Petropoulos et al. [96] and Carlson et al. [97] designed and evaluated a new generation of triangle models for high spatial resolution mapping of soil moisture in PA applications. One such technique is the optical trapezoid model (OPTRAM), which replaces the LST in the classic triangle model with short-wave-infrared transformed reflectance (STR). The moisture content of the soil in OPTRAM is calculated using the explanation of STR-VI space, similar to the classic triangle model [97]. Sadeghi et al.[98] used Sentinel-2 and Landsat-8 figures 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 prospective for providing precise soil moisture assessments than data gathered under the visible, NIR, and SWIR bands [93]. Signals in visible as well as near-infrared ranges had a lower penetrating ability than microwave signals, and are more susceptible to interference produced by atmospheric and cloud conditions [95]. For soil moisture measurement, sensors of microwave evaluate di-electric characteristics of soil surface mainly based on land surface smattering. The traditional microwave scanning radiometer-earth observing system (AMSR-E), soil moisture and ocean salinity (SMOS), soil moisture active passive (SMAP), and Sentinel-1 [93] have all been launched with active along-with passive microwave sensors for soil moisture observing. When compared with passive microwave sensors, active microwave sensors have a better spatial resolution. Active sensors, on the other hand, are subject to measurement errors owed to land surface coarseness and vegetation cover or canopy area [98]. Passive sensors, on the additional hand, were more precise and deliver high temporal resolution, but they have a rougher geographical resolution (e.g., 10s of kilometres) [99]. Typically, better resolution data is required for watershed and agricultural applications, predominantly PA [100].

11. NUTRIENT MANAGEMENT

An application of fertilizers must be done timely with suitable methods in order to take advantage for crop growth and yield whereas decreasing environmental impairment from loss of nutrients to groundwater and surface water. During establishing and succeeding phases of crop development, the suggested rate of fertiliser is commonly sprayed constantly. Due to variations in soil types, management, topography, weather condition, hydrology, crop fertiliser necessities vary geographically and temporally (during and between seasons) [101 and 102]. Using standard instruments like chlorophyll metres to map such fluctuation in status of crop nutrient for PA submissions might be difficult. Several remote sensing-derived vegetation indices (e.g., NDVI, SAVI) had been demonstrated to be considerably linked along-with plant chlorophyll, photosynthetic rate, and production of plant. Understanding the geographical diversity in crop nutrient status, that are critical for PA, can be aided by mapping these indices.

Numerous tractor-mounted remote sensors are available that might assess status of plant nutrient for present administration of spatially varying fertiliser amounts have recently become available. Commercially existing hand-held and tractor-mounted remote sensors which utilized crop reflectance information to estimate and spread over spatially variable fertiliser rates in real-time include Green Seeker, Yara N-sensor, and Crop Circle [103].

Remote sensors are frequently installed forward of the spray boom in tractor-mounted systems. In these systems, nitrogen (N) submission doses are estimated using vegetation indicators (e.g., NDVI), whose are then sent to a nutrient spreader for real-time fertiliser submission. The noted vegetation indices are converted into appropriate Nitrogen application doses using various algorithms. The N-application rates were estimated in general by associating with observed vegetation indices in the marked field to a reference vegetation index calculated in a healthy fertilised (N-rich) plot/strip that is indicative of the target field. Various fertiliser rate identification algorithms have been devised and effectively used in these marketally accessible sensors to record vegetation-indices based in-season nitrogen requirements for various crops [104,105].

Despite the commercialization of proximal remote sensing-based variable rate N-management technology, farmer acceptance remains stumpy in several agricultural companies [106]. The lack of unambiguous proof of considerable economic assistances (yield of crop and/or productivity), particularly in marketable farm settings (eg., large field areas), is a barrier to widespread implementation of these technologies [107]. Investigation is being undertaken with UAVs and several other remote sensors for a number of variety of crops in dissimilar climatic locations to advancement of these remote sensing based knowledge and enrich their benefits. Maresma et al. [108] investigated the usefulness of multiple vegetation indicators and height of crop is calculating in-season fertiliser treatment doses for maize produced in Spain using photos obtained by a UAV. Green Seeker and different crop circle sensors decrease nitrogen fertiliser use and boosted nitrogen efficiency for winter wheat cultivation in China, according to [109]. Overall, mapping based on remote sensing status of crop nutrients in the Pennsylvania might be boost crop nutrient use effectiveness whereas maintaining and increasing crop yields and also avoiding harmful off-site nutrient losses.

12. CROP MONITORING AND YIELD

Crop growth must be supervised in order to recognise the reaction of crop to environment and agronomic methods and to build successful fieldwork and/or remedy management programmes [110]. LAI and biomass accumulation are two important crop health and growth indices [111]. Several crop development and yield forecasting representations employ LAI as an input [112]. In-situ LAI assessment method are labour-intensive and time-taking, comparable to destructive field approaches for biomass approximation. Furthermore, these approaches do not produce a map of crop growth and biomass spatial variability [90 and 113]. Remote sensing figures on crop development and biomass might be used to gather useful information on site-specific properties (like, soil type topography etc.), management practices (viz. water, nutrient & other inputs), and several biotic as well as abiotic stresses (like, diseases, weeds, water, and nutrient stress) [114]. Remote sensing statistics can also be utilized to plot variations in tillage and residue management with their effects on crop growth and development. [115]. In a number of studies [116 and 117], hyper-spectral images paired to numerous machine learnings and cataloguing algorithms were used to record tillage and crop residue in agricultural extents. Such info on crop conditions and tillage practises could be help to plan scheme site-specific management, which may include adjustable irrigation. LAI and biomass had been projected by remote sensing figures for a variety of crops, involving row crops, several orchards, and vine crops [118, 119 and 120]. Normally, few research establish a regression or machine learning based approach to calculate LAI and/or biomass accumulation for research field by means of a collection of reference figures (e.g., calculated LAI and vegetation indices). Yue et al. [115] estimated bio-mass ($R2 = 0.74$) in several irrigation levels and fertiliser dose treatment plot during winter season of wheat cultivated in China using multiple spectral indices in combination with observed height of plant. For Kinnow mandarins produced in Pakistan, Ali et al [121] employed red-edge position (REP) recovered from hyperspectral images to estimate LAI ($R2 = 0.930$) along with chlorophyll amount ($R2 = 0.90$). REP is the location of the red-NIR slope's primary inflection point, which is instigated by significant chlorophyll absorption under red spectrum and canopy smattering in the NIR section [120]. Owed to intervention from the naked soil surface, accurate LAI estimate from reflectance records may be challenging, principally during early stage of crop growth. Improved vegetation indices corrected for soil and several other intrusions had been planned and utilized to evaluation LAI to address this constraint [122]. Red-edge constructed vegetation indexes had recently demonstrated to be useful for calculating LAI in a variety of crops [121]. There are two methods for estimating crop yields using remotely sensed data.

To estimate crop yield and biomass, biophysical factors resultant from remotely sensed facts are first utilized in a crop model. Second, arithmetical (e.g., regression) or realistic connections were established between crop parameters/indices which derivative from remote sensing (e.g., NDVI, LAI) and detected crop yield with biomass accumulation in a typical agricultural field area. 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 considerations, meteorological figures, yield and biomass data.

Maresma et al. [108] evaluated the association between maize crop yield, biomass accumulation and spectral indicators recorded during V12 phase 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 maximum connection with grain yields, similar to prior studies. In comparison to a single snapshot during the season, spatial mapping for crop biophysical characteristics or indices at frequent periods during the growing season is likely to provide a better estimate of crop biomass accumulation and yield [114].

13. CONCLUSION

The current study provided a comprehensive review of the function of remote sensing in assessing different water security challenges and other purposes. GIS is playing an increasingly important role in agriculture production around the world, helping farmers boost production, cut costs, and manage their land more efficiently, from mobile GIS in the field to scientific analysis of production data at the farm manager's office. The Internet of Things (IoT), Big Data analysis, and artificial intelligence (AI) are all the promising techniques that are being used to solve various problems, improve agricultural operations and inputs with the goal of increasing output while lowering costs.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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