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Remote Sensing as a Management and Monitoring Tool for Agriculture: Potential Applications

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Authors' contributions

This work was carried out in collaboration among all authors. Authors AA and LA conceptualized the manuscript, including method and approach to be used. Authors KF and SR outlined the manuscript. Authors IA, JNK and ES reviewed remotely sensed data. Author MUS contributed to the future recommendations of this manuscript. Authors SA, AN, RR and SN interpreted and drafted the manuscript vis-à-vis agriculture and revised it critically. All authors have read and agreed to the revised version of the manuscript.

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Review Article

ABSTRACT

Remote sensing technology has revolutionized agriculture management and monitoring by providing valuable information on crop health, soil conditions, weather patterns, and overall land management. The reflectance data are progressively being exploited in agriculture with the momenta gained in ground-based, airborne, and satellite remote sensing. The agriculture systems when managed conventionally don't facilitate the proper utilization of resources and productivity potential of the soil. However, taking the aid of remote sensing techniques helps in boosting the productivity potential of the soil and optimizing the inputs. This paper aims to review the potential applications of remote sensing in agriculture and its role in improving productivity, resource efficiency, and sustainability. The paper discusses various remote sensing techniques, including satellite imagery, aerial photography, and sensor-based data collection, and their integration with advanced data analysis methods. The applications explored include biomass estimation, yield estimation, global food demand, salinity stress detection, drought monitoring, soil moisture content assessment, and change detection. The paper highlights the benefits and challenges associated with each application and provides insights into future research directions and technology advancements in the field of remote sensing for agriculture.

Keywords: Agriculture; remote sensing; yield estimation; vegetation indices; satellite data; global food demand.

1. INTRODUCTION

Agriculture, which serves us with the most fundamental needs - food and fibre, has shown a transition from conventional to technology-intensive in the past century. Despite the fact that the world's population has been doubled and food demand has been tripled since 1960, global food demand has been met with only a 30% increase in cultivated land [1,2] and intensification of the inputs like fertilizers, pesticides which have a negative impact on environment [3]. By 2050, the global population is estimated to reach 9.7 billion in 2050 after reaching 7.7 billion in 2019 [4], while global food demand is projected to increase by about 56% [5]. However boosting agricultural production should be complemented with the sustained use of available resources and minimizing the negative effects on environment. The conversion of intensive agriculture to sustainable one must take place while taking into consideration the global changes due to unanticipated climatic conditions (e.g. changing in precipitation and temperature patterns) or extreme weather events [6].

Remote sensing (RS), a technology that enables the acquisition of information about Earth's surface without coming in contact with the objects under surveillance [7], has emerged as a valuable tool for agricultural management and monitoring. Traditionally, agricultural management relied on manual observations, labor-intensive fieldwork, and subjective assessments. However, these methods often provided limited spatial coverage, lacked real-time monitoring capabilities, and were prone to human biases. The integration of remote sensing techniques in agriculture has revolutionized traditional farming methods by providing a wealth of information at various spatial and temporal scales [8]. This technology allows for the collection of data from large agricultural landscapes, facilitating a comprehensive understanding of crop dynamics, environmental factors, and land use patterns, and can serve as an early warning system [9], thereby boosting crop yield by increasing input efficiency [10] and hence reducing environmental footprint.

The agricultural production is governed by many factors including seasonal changes, physical settings (type of soil, nutrient and water availability), and management practices [11], which exhibit huge spatial and temporal variability. Hence, timely monitoring of these factors along with raised crop is vital for maximising crop yield and preventing crop failure. Many problems are encountered while monitoring agricultural activities, not prevalent in other economic sectors, thereby making it imperative to exploit RS technology [12]. This can substantially contribute to provide an accurate and apt portrayal of the agricultural sector on account of its huge spatial coverage with high revisit frequency [13,14].

RS has found its applications in diverse areas encompassing resource mapping, land use pattern detection, geo-hydrological investigations, flood and drought monitoring [15]. The agro-meteorology has also benefitted from RS techniques in different ways which include ascertainment of cloud surface temperatures [16], land surface temperature [17,18], precipitation [19], radiation [20], soil moisture [21], crop yield [22], and so on. Moreover, this technology finds its utility even in monitoring the pest and disease incidence [23]. RS in conjunction with the crop simulation models are valuable instruments in forecasting crop yield [24,25].

This review impresses upon the indispensable role of RS in agriculture. In first section (section-2), the theoretical background of the application of remote sensing in agriculture is discussed in which vegetation indices are discussed in detail. A detailed sub-section has been devoted to vegetation indices, the reason being their high relevance with bio-physical features of plants, and lesser relevance to the factors impeding interpretation of RS data. In latter section (section-3), evolution of the different platforms employed for RS data acquisition have been discussed in detail. The applications of RS in agriculture have been reviewed in latter section (section-4) under proper headings. Seven important applications have been discussed: 1) Biomass estimation, 2) Yield estimation, 3) Global food demand, 4) Salinity stress detection, 5) Drought monitoring, 6) Soil moisture content assessment, and 7) Change detection. The main focus has been devoted to sub-section “Yield estimation” because of its role in agricultural sustainability and global food demand.

2. THEORETICAL BACKGROUND

The theory basis of remote sensing applications in agriculture lies in the interaction between electromagnetic radiation and agricultural features such as vegetation, soil, and water. Understanding these interactions is crucial for extracting meaningful information from remotely sensed data and utilizing it for agricultural purposes. The information dispensed by RS is carried by electromagnetic (EM) radiation, which traverses its path in vacuum in the form of waves of varying wavelengths at the speed of light. RS exploits a portion of EM spectrum covering visible, Infra-red (IR) (shortwave – SWIR, near – NIR and thermal – TIR) and microwave bands [26]. Spectral signatures represent the unique reflectance patterns of different agricultural features across the electromagnetic spectrum [27]. These signatures are determined by the absorption and reflection properties of the features. They are used to distinguish vegetation from bare soil, water, and other similar features based on the responses of the targets to these wavelength regions (see Fig. 1). The spectral signature graph is stored in the spectral signature library in a digital database to avoid loss of the data and provide easy access to researchers worldwide [28]. By comparing the spectral signatures of vegetation, soil, and other agricultural components with known spectral libraries, RS can identify and discriminate between different land cover classes and monitor their changes over time. Another approach of tapping information from RS is Vegetation Index (VI). Vegetation Indices (VIs) are quite simple and effective algorithms for quantitative and qualitative evaluations of vegetation cover, visor, and growth dynamics, among other applications [29].

2.1 Vegetation Indices (VIs)

The biological and physical characters of plants can be differentiated spectrally via VIs termed as unitless radiometric quantities [30]. They are computed in terms of differences/ratios of two or multiple bands of SWIR, NIR and visible wavelengths [29]. The expediency of VIs can be established on account of their high relevance with bio-physical features of plants, and lesser relevance to the factors impeding interpretation of RS data which include atmosphere, soil background, relief, viewing, illumination geometry and non-photosynthesizing elements of plants [31].

The pioneer among VIs was proposed by [32], namely Ratio Vegetation Index (RVI). RVI, ratio of red to IR wavelength, being highly sensitive to vegetation and bearing good correlation with plant biomass, is broadly expended for monitoring and estimation of green biomass estimations explicitly at high vegetation coverage [29]. The Normalized Difference Vegetation Index (NDVI) which was proposed by [33] is the most frequently implemented index [34], and is computed as a ratio of the difference to sum of the NIR and Red reflectance [26]. NDVI time series data have been efficaciously employed in diversified applications encompassing global change detections, growth monitoring and yield prediction of crop, phenological studies, desertification and drought monitoring, wildfire assessment, and biogeochemical and climatic modeling [23].

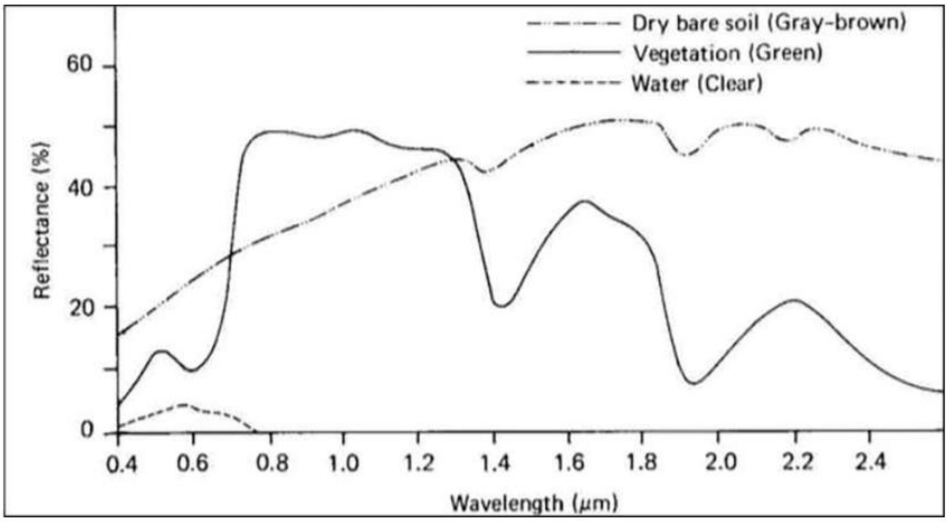

Fig. 1. Typical spectral reflectance curves for dry bare soil, vegetation and water
(Source: [7]

Table 1. Repository of vegetation indices

Index	Formula	Wavelengths [nm]	Application
Advanced Normalized Vegetation Index	$ANVI = \frac{NIR - BLUE}{NIR + BLUE}$	BLUE: 400 – 500 NIR: 700 – 900	Mapping *Ridolfia segetum* patches in sunflower crop [41].
Aphid Index	$Al = \frac{NIR1 - NIR2}{RED1 + RED2}$	RED1: 712 RED2: 719 NIR1: 761 NIR2: 908	Aphid infestation in wheat [42] and mustard [43]
Chlorophyll Index	$CI = \frac{NIR}{GREEN} - 1$	GREEN: 520 -600 NIR: 760 - 900	Nitrogen status [44], Nitrogen status and productivity [45].
Continuum Removed (CR) Spectral Index	$A_{CR(1200)\ at\ leaf\ level} = \int_{\lambda 1116}^{\lambda 1284} 1 - \left(\frac{NIR}{NIR_{CR}}\right)$ $A_{CR(1200)\ at\ clandscape\ level} = \frac{(NIR1 - NIR2)(1 - \frac{NIR3}{NIR_{CR}})}{2}$	NIR: 1116 – 1284 NIR1: 1267 NIR2: 1156 NIR3: 1210	Leaf and canopy water content in poplar [46], Leaf water content in Oak [47].
Damage Sensitive Spectral Index	$DSSI = \frac{RED - NIR - BLUE - GREEN}{(RED - NIR) + (BLUE - GREEN)}$	BLUE: 509 GREEN: 537 RED: 719 NIR: 873	Pest incidence on wheat [48].

Index	Formula	Wavelengths [nm]	Application
Effective Leaf Area Index	$ELAI = -0.441 + 0.285\frac{NIR}{RED}$	RED: 610 – 680 NIR: 780 – 890	Yield prediction [49].
Green Normalized Difference Vegetation Index	$GNDVI = \frac{NIR - GREEN}{NIR + GREEN}$	GREEN: 557–582 NIR: 720 – 920 and/or GREEN: 520 – 600 NIR: 760 – 900	Corn yield prediction [50], Rice Yield [51], Disease detection [52].
Green Red Vegetation Index	$GRVI = \frac{GREEN - RED}{GREEN + RED}$	GREEN: 500 - 590 RED: 620 - 700	Phenological indicator [53], pest incidence [54].
Healthy-Index	$HI = \frac{GREEN - RED1}{GREEN + RED1}0.5RED2$	GREEN: 534 RED1: 698 RED2: 704	Early disease detection [55].
Leaf Rust Disease Severity Index 1 Leaf Rust Disease Severity Index 2	$LRDSI_1 = 6.9\frac{RED1}{BLUE} - 1.2$ $LRDSI_2 = 4.2\frac{RED2}{BLUE} - 0.38$	BLUE: 455 RED: 605 RED: 695	Diseased detection [56].
Modified Soil adjusted Vegetation Index	$MSAVI2 = 0.5[2NIR + 1 - \sqrt{(2NIR+1)^2 - 8(NIR - RED)}]$	RED: 630 – 690 NIR: 760 – 860	Nitrogen content [57].
Normalized Difference Infrared Index	$NDII = \frac{NIR - SWIR}{NIR + SWIR}$	NIR1: 845 – 885 NIR2: 1650 –1700	Canopy water content variation [58].
Normalized Difference Vegetation Index	$NDVI = \frac{NIR - RED}{NIR + RED}$	NIR: 700 – 900 RED: 610-680	Biomass estimation [59,60], Water stress in wheat [61], Disease incidence [62], Yield [63].
Normalized Difference Water Index	$NDWI = \frac{NIR1 - NIR2}{NIR1 + NIR2}$	NIR1: 841 - 876 NIR2: 1230–1250	Plant water content [64,65].
Normalized Pigment Chlorophyll Ratio Index	$NPCI = \frac{RED1 - BLUE1}{RED2 + BLUE2}$	BLUE: 460 RED: 660	Leaf chlorophyll content [66].
Optimized Soil-Adjusted Vegetation Index	$OSAVI = \frac{NIR - RED}{NIR + RED + 0.16}$	RED: 640 – 720 NIR: 770 – 880	Nitrogen status [67].
Ratio Vegetation Index	$RVI = \frac{NIR}{RED}$	RED: 630 – 690 NIR: 760 - 900	Nitrogen status [68], Pest-induced stress [69].
Red edge normalized difference vegetation index	$RENDVI = \frac{R_{NIR} - R_{red\ edge}}{R_{NIR} + R_{red\ edge}}$	NIR: 760–850 $R_{red\ edge}$: 690–730 nm	Yield [70] Irrigation management [71], disease [72].
Relative Reflectance Index	$RRI = \frac{NIR_a/VIS_a}{NIR_r/VIS_r}$	Visible: 400 – 700 NIR: 740 - 820	Drought stress [73].
Shortwave Infrared Water Stress Index	$SIWSI(6,2) = \frac{SWIR - NIR1}{SWIR + NIR1}$ $SIWSI(6,2) = \frac{SWIR - NIR2}{SWIR + NIR2}$	NIR1: 841 - 876 NIR2: 1230 - 1250 SWIR: 1628 - 1652	Canopy water content [74].
Simple Ratio	$SR = \frac{RED}{NIR}$	RED: 648 NIR: 747	Pest infestation on regional scale [75]

Index	Formula	Wavelengths [nm]	Application
Soil adjusted vegetation index			Yield [76], Biomass [77]
Structure Insensitive Pigment Index	$SIPI = \frac{NIR - BLUE}{NIR + RED}$	BLUE: 445 RED: 680 NIR: 800	Pest incindence on wheat [48].

Numerous researches have been conducted to frame more indices moderating the atmospheric and soil background influence on the outcomes of spectral measurements. SAVI (Soil Adjusted Vegetation Index) [35] is such an illustration of the VI restraining the sway of soil background on remotely detected vegetal cover. An example akin to this is index termed as VARI (Visible Atmospheric Resistant Index) [36]. This index intensely lessens the effect of the atmosphere. However, many indices have been established to deliberate differences in reflectance for the NIR and SWIR wavelengths, which designate the manifestation of deficiency of water in plants e.g. WI (Water Index) [37] and SIWSI (Shortwave Infrared Water Stress Index) [38]. In order to account for association of water stress with thermal characteristics of plant, the indices such as SI (Stress Index Water) [39] and WDI (Deficit Index) [40] have been established. More than hundred VIs derived from multi-spectral imageries have been reported [29]. The few VIs used for particular agricultural applications, which are reported in the literature are presented in Table 1.

3. DEVELOPMENT OF PLATFORMS of RS TECHNOLOGY

There are three different platforms of applying RS technology in agriculture [26]: 1) Ground-based, 2) Airborne, and 3) Space-borne satellites. All of the platforms have some pros and cons, and the choice of the method is driven by the scale and purpose of survey [78].

The Ground-based RS method makes use of field-scale sensors, either handled by hand or mounted on any machine [3] to monitor both biotic and abiotic stresses in crop. Benefits of this method include a better temporal, spatial, and spectral resolution [26,3]. However, the limiting factors in this technique are the efficiency, scale and labour involved which limits its applicability to only lesser areal extents, while airborne and satellite-based RS methods are apt for larger areal extents [26].

The second platform is Airborne RS, which engage manned aircrafts and drones (unmanned aerial vehicles (UAVs)) to offer pictorial crop inventory on time. The choice of equipment to be used is governed by the budget allocations. A typical UAV comprises of a communication and navigation systems with several sensors on-board [79]. UAVs are light weight, lesser cost intensive and low speed instruments; thereby replacing the manned aircrafts. There exist two types of UAVs: the first one being the 'fixed wing' and the other one 'rotary wing' [26], the flight time of each UAV depends on the payload weight. The former with light weight (300 gms) HD cameras as payload, can fly at high speed for longer duration (2 hours) and does not entail a pre-requisite of a launcher or a runway, whereas the latter can easily hover over an object with briefer flight time (15-25 min) due to its high battery power consumption for greater payload weight [79]. Table 2 tabulates various common UAVs employed for agricultural purpose, in particular for remote crop health monitoring [80].

UAV platform is cost effective and flexible, thereby offers an excellent alternative to airborne and satellite. UAVs produce imagery of high resolution [81] because of its capability of covering target repetitively and faster at different altitudes and times. Consequently, the UAV can even discern variations among plants within the field [82]. The detailed information regarding the utility of UAVs in the agriculture has been thoroughly reviewed by [83,81,84,85 and 86].

The final platform is space-borne-based RS, which is being categorized on the basis of timing and orbit taken by a satellite [14]. The data sensed by this satellite is applicable for larger geographical regions [87], which can therefore monitor crops at both global and regional levels. Furthermore, it can be used locally for providing important crop coverage, mapping, classification, and yield forecasts [26]. The disadvantage of this method is that it is affected by the meteorological conditions [88], atmospheric noise [78], and can be cost ineffective. Moreover, satellites have an average high revisit time in days (e.g., 16 days for Landsat and 26 days for SPOT) which limits its applicability in agriculture, in particular nutrient and irrigation scheduling [29].

Table 2. UAV platforms used in agriculture [14]

Model	Manufacturer	Aircraft Power/Type	Power	RS Sensors	Weight (kg)	Flight Time (min)	Flight Speed (m/s)
Aibot X6	Aibotix	Hexacopter	Electric	Camera	4.6–6.6	30	14
AeroHawk	Hawkeye UAV	Fixed-wing	Electric	Camera	5.1–5.8	90	16.5–19.5
Delta X8	Altus UAS	Octocopter	Electric	Camera/LiDAR	9.5	10–14	12
eBee RTK	senseFly	Fixed-wing	Electric	Camera	0.7	40	11–25
Geocopter	IGI	Helicopter	Gas	Camera/LiDAR	90	120–180	NA
Li-AIR	TRGS	Hexacopter	Electric	LiDAR	6.9–9.5	15	8
MD4-1000	Microdrones	Quadrocopter	Electric	Camera/LiDAR	6.0	90	12
OnyxStar FOX-C8 HD LiDAR	Altigator	Octocopter	Electric	LiDAR	9.2	20	14
Puma AE	AeroVironment	Fixed-wing	Electric	Camera	6.1	210	23
Phantom 2	DJI	Quadrocopter	Electric	Camera	1.3	25	15
Pteryx	Trigger Composites	Fixed-wing	Electric	Camera	5	120	12.5–15
Ricopter	Riegl	Octocopter	Electric	LiDAR/camera	25	30	22
RS-16	American Aerospace	Fixed-wing	Gas	Camera	38	720–960	33
Scout B1-100	Aeroscout	Helicopter	Gas	LiDAR	77	90	NA
SIRIUS PRO	Topcon	Fixed-wing	Electric	Camera	2.7	50	18
UX5	Trimble	Fixed-wing	Electric	Camera	2.5	50	22

Some satellites provide free data, while others offer commercial solutions. Pleiades-1, a commercial solution, generates high-resolution images having one day as temporal resolution. The most commonly used satellites for obtaining hyperspectral imagery are Sentinel and Landsat-8 providing free solutions, and QuickBird providing commercial solution [14]. Even though the temporal resolution of Landsat-8 is larger than QuickBird, it provides multi-spectral images with 11 bands. Another widely used satellite, Sentinel has 3 missions, i.e., Sentinel-1, Sentinel-2 and Sentinel-3.

Sentinel-1 has a great potential for mapping crop which is attributed to quick response of SAR to vegetal structure and water content, insensitivity to cloud cover, and high revisit frequency having 6 days gap. By expending multi-temporal and dual-polarization feature of SAR data, Sentinel-1 provides accurate (85% accuracy) crop maps. Among many products generated by this mission, the most exploited for agriculture is the IW Level-1 GRDH product, which needs intensive pre-processing procedure involving calibration, co-registration, multi-looking and geocoding [89]. Sentinel-2 mission with its high spatial resolution (10 – 20 m), high revisit frequency (5 day), global coverage, and compatibility with Landsat series, has a great potential for monitoring agrarian fields both at regional and global level. The operational feature of this Sentinel-3 mission indicates highly available data products with faster delivery time, which are its key design drivers [90].

4. APPLICATIONS OF RS IN AGRICULTURE

4.1 Evaluation of Biomass

The spectral as well as structural properties of the target can be acquired by RS at various spatial and temporal scales, hence making it the best possible method for huge area biomass evaluation [91]. For crop growth monitoring, precise estimation of above ground biomass (AGB) is very essential [92]. Presently, satellite and/or ground based RS are utilized for AGB evaluation [91]. Scalability issues can arise while using ground-based RS as it being labour-intensive and time-consuming. However, satellite RS may not make available adequate data resolution for its applicability in precision agriculture [92].

Another technique used to estimate biomass is LiDAR (light detection and ranging). LiDAR data has grasped more consideration owing to its robustness in biomass estimation for the reason that it triumphs over the data saturation flaw of Landsat [93]. LiDAR provides a precise CSM (crop surface model) owing to its high spatial resolution, thereby permitting the biomass estimation using plant height [94], while its applicability is limited to small areas only as its processing requires intensive computational resources [95]. The gap existing between terrestrial and satellite has been filled by UAVs and lightweight sensors, the promising tools for precision agriculture. Recently, the physical plant factors, for instance plant height, have turned out to be focus of UAV-centered RS methods for crop monitoring. Plant height obtained from canopy surface models (CSMs) at different temporal scales has been deliberated as a robust parameter for biomass estimation [96]. Besides CSMs, multi- and hyper-spectral images and RGB images, obtained for UAV have been pooled with CSMs to evaluate biomass [97].

From 2D images overlapped in succession and acquired by an UAV using the Structure from motion (SfM) algorithm, three-dimensional (3D) point clouds are generated which offer new options for the acquirement of crop surfaces [92]. SfM, a computer based technology, produces 3-D geometry by repeated bundle adjustment and image matching techniques [98]. 3D point clouds which are derived from CSMs contain crop canopy vertical distribution information, which can be utilized for crop observance, e.g., plant height measurement [99], yield prediction [100] and biomass estimation [101].

A type of digital elevation model (DEM) derived from point clouds is triangulated irregular network (TIN) which symbolizes the surface with a sequence of unremitting, non-overlapping, asymmetrical triangles by means of the Delaunay triangulation algorithm [102]. For crown volume extraction TIN can be utilized efficiently [103]. In contrast to gridded DEM, TIN is capable of showing surface structure particulars more precisely and more proficiently without the interruption process [104]. Moreover, the information deciphered by TIN is more detailed and not restricted to plant height only; signifying extra comprehensive structural information should be tapped for AGB assessment [92]. The performance of multispectral in conjunction with structural features for AGB assessment is better than using them alone, which is further enhanced by using meteorological features [92].

4.2 Yield Estimation/ Prediction

The yield estimation of crop is of great significance not only to farmers but also to government bodies and policy framers so as to boost the agricultural productivity and spot the abiotic and biotic threats affecting the crop productivity [105]. The site specific yield estimation of crop helps to discern the spatial variability of crop vigor within the plot and thereby, aids in optimizing management strategies and minimizing the crop threats [106].

The forecasting of crop yield using RS technology is principally based on the empirical/statistical relationships existing between yield and VIs [107]. Of all the indices developed so far, NDVI being closely associated with the vegetation vigor [108], is most commonly used to ascertain the crop condition, developmental phases, biomass, and consequently yield [26]. The green leaf area index (LAI) of few crops has been reported to have asymptotic non-linear relationship with NDVI [109,110]. Different LAI values indicate dissimilar intercepted wavelengths which have direct bearing on the biomass generation which in turn are indicative of crop yield [108]. Moreover, NDVI entails most of the gen on precipitation and can explain most of the grain variability, e.g., in wheat [111].

However, the empirical models which estimate yield tapping RS data are limited to those regions only where they have been calibrated [112]. But yet they are used commonly because they are less data intensive and easy to employ at regional level [113]. For an accurate estimation of crop yield at regional level, many researchers have integrated spectral data with crop growth simulation models [114,115], but these models are very data-intensive encompassing soil properties, crop management practices, crop parameters and agro-meteorological data.

The Ground-based RS apparatuses have been expended successfully for forecasting the yield of many crops- rice [116], wheat [117]. The determination of accurate yield predictions in heterogeneous agricultural landscapes using satellite data is dependent upon the resolution of sensors as well as other exogenous factors. The freely available sensors like the AVHRR (Advanced Very High Resolution Radiometer) are appropriate for detecting vegetation changes, on account of the high temporal resolution, however spatial resolution of these sensors is low of the order of >8 km which reduces its efficiency in estimating the crop yield in heterogeneous land settings. Moreover, most of the farmer land holdings are smaller than the pixel size of sensor, hence making AVHRR difficult to use for yield estimation. The significant advances in the field of RS technology gave rise to successor sensors such as MODIS, an improvement over AVHRR [118], especially in terms of spectral and spatial resolutions. MODIS was explicitly aimed for land-related studies [16] allowing foliage monitoring at regional level [108].

The yield estimates using MODIS data have been found to be more precise than AVHRR data, when applied on the comparatively homogeneous fields [119]. The MODIS has an improved spectral resolution (36 spectral bands); however, 250 m spatial resolution is still coarser for heterogeneous settings. On account of these limitations, sensors with improved spectral, temporal and spatial resolutions like Landsat series were framed, which offered an apt substitute to MODIS and AVHRR for crop yield prediction. The Landsat 8 OLI having spatial resolution of 30 m is such an example. However, it suffers from the major drawback of fairly long temporal resolution, having periodicity of 16 days, confining the number of observations taken in a crop growing season, which is further fuelled by cloud cover limiting the successful sensing [119]. In spite of this limitation, Landsat series (e.g. TM and ETM+) with revisit frequency akin to Landsat 8 OLI have been reported to provide fairly accurate yield estimation, when applied to the homogeneous agricultural systems [120,121] Landsat 8 OLI sensors have been even found suitable for heterogeneous African cropping systems for capturing phonological stages of maize [11].

The uninterrupted developments of multi-spectral remote sensors have geared the launch of the new technological generation of free sensors like Sentinel 2 with high temporal resolution of 5 days, spectral resolution of 13 bands, and spatial resolution of 10 m resolution [12]. These can be applicable in highly fragmented cropping systems [122]. There are many more sensors having high spatial and temporal resolutions encompassing ASTER, ALI, IRS series, SPOT, EROS, KOMOS, CARTOSAT-1, GeoEye-1, WorldView-1, FORMOSAT-2, KOMPSAT-2 IKONOS, OrbView-3 and QuickBird. The highly fragmented cropping systems need higher spectral resolution data providing detailed information of crops which is provided by hyperspectral sensors, the review of which is provided in detail by [123]. However, it is incumbent here to mention though hyperspectral sensors have high spectral, spatial and temporal resolution, they generate voluminous data which limits its applicability to larger areal extents [124].

4.3 Global Food Demand

Globally per capita food demand is strongly linked with per capita Gross Domestic Product (GDP) [125] (Fig. 2). For instance, the richest countries (group A e.g. US) consume approximately 8,000 kcal·day^{-1} in comparison to the groups C and D (Brazillian and Indonesian people, respectively) consuming 4,000 kcal·day^{-1}. While considering this and presuming that both GDP as well as global populace will endure to proliferate in the future, the earlier trend of intensely escalating food pressure is projected to persist for 3–4 decades [126]. [125] envisage that crop caloric/protein demand per head will duple between 2005 and 2050.

The crop data procured using RS technology has great potential towards monitoring of food quality and demand, by affording well-timed, synoptic, cost effective and recurring gen [16]. The crop acreage and production are the two elements

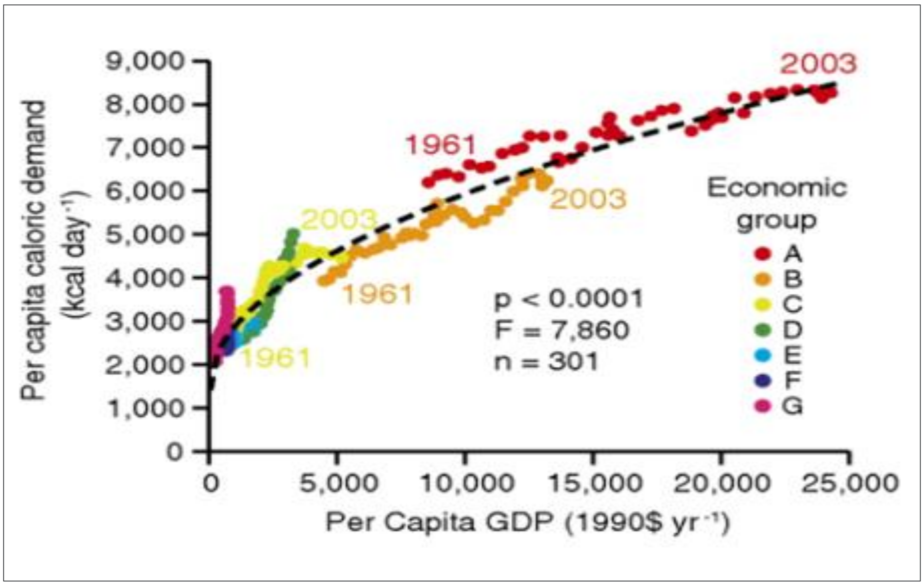

Fig. 2. Yearly dependence of per capita crop caloric demand on per capita GDP for different economic groups
[Source: 125]

that can be assessed from the data procured from present RS satellites. Moreover, the crop phenology, stress conditions and disturbances can also be detected [126]. The climatic extremities as expected in future have a greater sway on agricultural production, which need to be continuously monitored for risk assessment at both spatial and temporal scales, which is only possible by the aid of RS techniques.

The two approaches of RS, microwave RS-based backscattering and optical RS-based surface reflectance, are employed for both mapping as well as forecasting activities [126]. The nation must have repository of fast and reliable food forecasts prior to the harvesting of the crop irrespective of the method employed (RS/ground-based). Food production forecasts employing RS techniques may aid governments, decision, and policy makers to devise suitable strategies- to quantify the amount of food to be imported in case of deficiency or the amount of food to be exported in case of surplus [127] and to procure the food at cheaper rates from other nations without deciphering the information about the shortfall of food in near future.

4.4 Salinity Stress Detection

The saline conditions of the soil have negative bearing on soil and water quality causing land degradation which in turn impedes crop growth, and hence crop production. Not only crop mapping and monitoring is taken over by RS technology, but crop stresses induced due to saline conditions can also be figured out with RS [128]. The RS technology can help in identification of salt traits discernable on soil surface, e.g., white crust, a direct indicative of soil salinity [129]. Alternatively, indirect ascertainment of soil salinity is done using different indicators, e.g., presence of halophytes and active salt-tolerant crops [130,131]. Many researchers have attempted to monitor and map soil salinity areas using multispectral sensors [132,133] and hyperspectral sensors [134,135,136]. The hyperspectral sensors have precedence over multispectral sensors with respect to detection of salt characteristics on soil surface, and distinction between halophytes and non-halophytes on account of high spatial resolution of hyperspectral sensors [134].

4.5 Drought Monitoring and Assessment

Drought is a complex hydro-meteorological phenomenon [137] occurring due to diminution of precipitation over prolonged period of time, causing reduction in the soil moisture [138]. Drought exhibits multiple manifestations and is classified into different types: meteorological drought, agricultural drought, and hydrological drought [139]. The most commonly used approach for characterization and monitoring of drought is drought index [140]. An inventory of drought indicators and indices, and their applicability has been presented by World Meteorological Organization (WMO) and Global Water Partnership (GWP) [141]. The precipitation is a key meteorological factor that has a predominant effect on the occurrence and characterization of drought via drought indices [142]. Precipitation data embodies large spatial and temporal variation [143] which cannot be interpolated always exactly. The efficiency of drought indices is highly dependent on the number of rain gauging stations in an area [144] which hampers the drought assessment in regions with limited number of rain-gauges. The progresses of RS techniques have enabled the procurement of precipitation data at varying spatial and temporal resolutions and have been globally used for drought forecasting [143]. The deficiency in precipitation, i.e., meteorological drought, causes deficiency in soil moisture referred to as agricultural drought [145]. The agricultural drought can be monitored by RS either by assessing soil moisture status or by assessing the different indices based on vegetation [146] e.g., NDVI, Evaporative Stress Index (ESI), Enhanced Vegetation Index (EVI), Vegetation Health Index (VHI), Vegetation Condition Index (VCI) and Soil Adjusted Vegetation Index (SAVI) [147].

4.6 Soil Moisture

The estimation of soil moisture is imperative for water budgeting, agro-meteorological applications, and forecasting natural upheavals including droughts, floods, soil erosion and dust storms. Nevertheless, precise in-situ measurement of soil moisture is quite capital intensive and time consuming because it entails repetitive soil sampling to evaluate the continual vicissitudes in soil moisture. A better alternative to the conventional methods of soil moisture determination is RS approach which gives synoptic view of large areas along with the spatial and temporal variations [148].

The soil moisture content is remotely sensed employing near gamma radiation, microwave, TIR, IR and visible radiation. Nevertheless, owing to ground penetration and all-season proficiency of active and passive microwave radiations, they corroborate to be the most pledging techniques. The main hurdle in the functioning of rest techniques is hindrance due to cloud cover. Although, the data sensed remotely by microwave radiations is quite promising but its exposition is very complex owing to vegetal cover, surface roughness, textural and geometrical properties of soil [21].

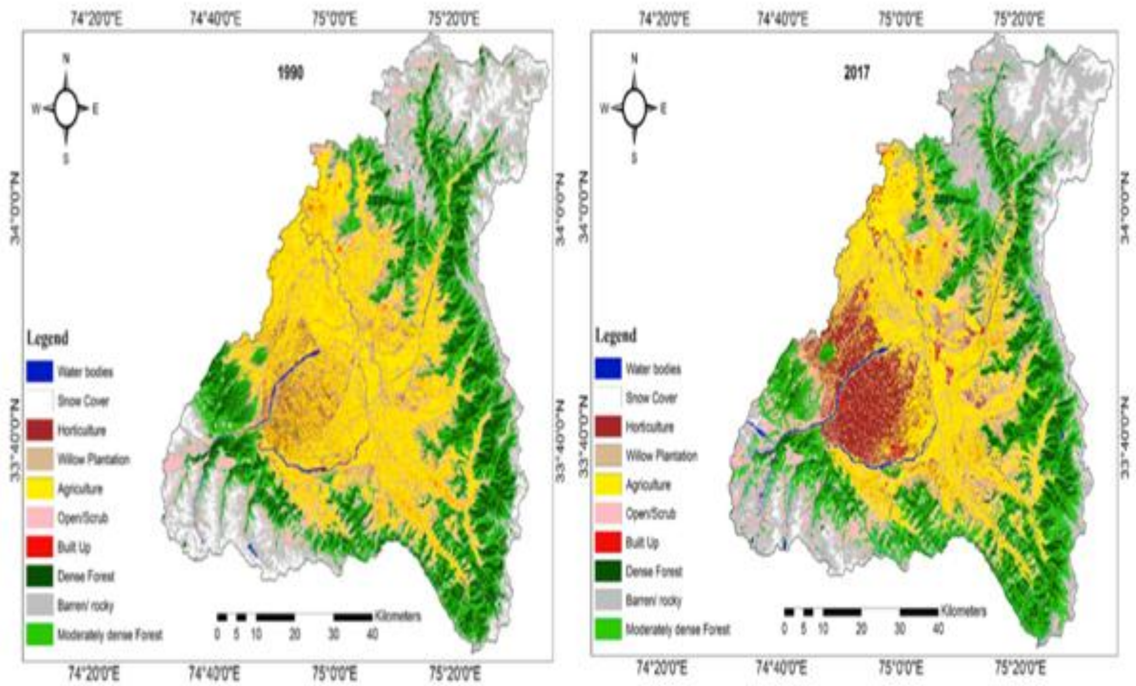

Fig. 3. Land use land cover change of Southern Kashmir Himalaya, J&K, India at different temporal scales [149]

4.7 Change Detection

The land use on sustainable basis plays a vital role in food security. Change detection in purview of land use land cover (LULC) change has great implications on food security of a region because of frequent shifts of agricultural land to other land uses. The satellite-based RS data have been successfully employed for mapping LULC patterns and changes. LULC change studies can cater policy makers by serving as an input for devising an effectual land use policy for a region. An example of LULC change study for the Southern Kashmir Himalaya, J&K, India, is manifested in Fig. 3, in which the exorbitant shift of agricultural land to horticultural land has been corroborated over the period of 27 years [149].

5. CONCLUSIONS AND FUTURE RECOMMENDATIONS

The review expounds the robust role being played by RS in the agricultural sector. By leveraging the power of remote sensing techniques, such as satellite imagery, aerial photography, and sensor-based data collection, farmers and agricultural stakeholders can optimize resource utilization, enhance productivity, and promote sustainability. One of the paramount pros in using remote sensing data is its efficiency to empower agricultural actors in addressing global issues such as biodiversity loss, land degradation, and climate change. This review paper provides a comprehensive overview of few potential applications of remote sensing in agriculture and highlights its significance in improving productivity, resource efficiency, and sustainability. It has explored the use of remote sensing for biomass estimation, yield estimation, addressing global food demand, detecting salinity stress, monitoring drought conditions, assessing soil moisture content, and detecting changes in agricultural landscapes. Each application has been discussed in terms of its benefits and challenges, highlighting the value that remote sensing brings to agricultural practices. RS technology has been effectively tapped by different researchers in gauging crop parameters and forecasting crop yield. RS data has capacitance of even gauging vegetation anomalies like drought conditions and salinity stress conditions which have significant effects on the crop yield. This information generated by RS plays a great role in global food demand forecasting which can help policy makers and government to devise plans for procurement of food supplies in case of dearth and managing agricultural productivity.

The integration of remote sensing with advanced data analysis methods, such as artificial intelligence (AI) and machine learning (ML), holds significant promise for enhancing the capabilities of decision support systems in agriculture. This integration can bring about more accurate, efficient, and automated analysis of remote sensing data, leading to improved resource allocation and targeted interventions. There are many areas which still need major overhaul or changes in existing RS systems as well as methods and techniques to derive meaningful results from RS imageries. Modern satellites need an upgradation in terms of sensor specifications which can address the spatial and temporal crop yield estimation at much higher spatial scales addressing SDGs of poverty reduction, zero hunger, good health and wellbeing, and overall sustainability. Forecasting climate and crop yield has been a major problem in developing and under developed parts of the world which minimizes the resilience of societies towards impending disasters. Atmospheric disturbances in high altitude areas are very frequent which reduces their efficacy in agricultural studies, thus RS systems need more robust algorithms to reduce the atmospheric distortions. Furthermore, we suggest that to achieve UN SDGs, access to the RS data is necessary, which still is not available to most of the end users especially the high resolution data. Mechanisms need to be put in place for better and easy access of satellite data.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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