# Chapter 1
# Geospatial Technologies for Crops and Soils: An Overview

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## Contents



**Abstract** Natural resource monitoring and assessment is a vital step to formulate a sustainable development plan. The introduction of various modern geospatial techniques and tools like Remote Sensing (RS), Geographic Information System (GIS), Global Positioning System (GPS), and information technology (IT) have provided

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powerful approaches of surveying, identifying, classifying, mapping, monitoring, and characterization of the composition, extent, and distribution of various natural resources. Geospatial techniques deal with the acquirement, storage, processing, production, presentation, and dissemination of geoinformation. The information obtained from RS, GPS, and through conventional methods could be used effectively to create database in GIS platform for various spatial and temporal analysis related to sustainable management of land resource and formulate environment-friendly action plans. Major applications of geospatial technologies related to crops and soils are crop inventory and monitoring, crop production estimates and forecasting, crop growth simulation modeling, crop yield estimation, precision agriculture, soil mapping, land degradation assessment, soil erosion assessment, soil quality assessment, digital soil mapping, digital terrain modeling, soil-landscape modeling, land use/land cover mapping, agricultural land use planning, etc., which have a far-reaching impact on mapping, monitoring, and management of crop and land resources on sustainable basis. Geospatial approaches have made inroads across different sectors both in private and public domain in various countries across the world. Selected tools can help to restore the soil health, stop exploitation of the natural resources, reduce energy consumption, carbon and water footprints, and improve the productivity and sustainability under changing climate. Geospatial technologies for crops and soils a novel tool for the food, nutritional, environmental, and economic security for the future generations under limited natural resources. This book will be helpful for the producers, researchers, teachers, and policymakers to deal with the future alarming issues.

**Keywords** Agriculture · Geospatial · Geographic Information System · Information Technology · Remote Sensing

## Abbreviations

| | |
|---|---|
| AI | Artificial Intelligence |
| ALOS | Advance Land Observing Satellite |
| APEX | Airborne PRISM Experiment |
| AVIRIS | Airborne Visible Infrared Imaging Spectrometer |
| CA | Conservation Agriculture |
| CNSA | China National Space Administration |
| CSA | Climate-Smart Agriculture |
| DESIS | DLR Earth Sensing Imaging Spectrometer |
| DGPS | Differential Global Positioning System |
| EM | Electromagnetic |
| ENVISAT | Environmental Satellite |
| ESA | European Space Agency |
| EWT | Equivalent Water Thickness |

| | |
|---|---|
| FAO | Food and Agricultural Organization |
| FAPAR | Fraction of Absorbed Photosynthetically Active Radiation |
| GHGs | Greenhouse Gasses |
| GIS | Geographical Information System |
| GPS | Global Positioning System |
| HSI | Hyperspectral Imager |
| ISRO | Indian Space Research Organization |
| IT | Information Technology |
| JAXA | Japan Aerospace Exploration Agency |
| LAI | Leaf Area Index |
| LANDSAT | Land Satellite |
| MODIS | Moderate-resolution Imaging Spectrometer |
| MRS | Microwave Remote Sensing |
| NASA | National Aeronautics and Space Administration |
| NAVSTAR | Navigation System with Time and Ranging |
| NDRI | Normalized Difference Red Edge Index |
| NDVI | Normalized Difference Vegetation Index |
| NIR | Near Infrared |
| PA | Precision Agriculture |
| PALSAR | Phased Array Type L-band Synthetic Aperture Radar |
| PF | Precision Farming |
| RDVI | Renormalized Difference Vegetation Index |
| RISAT | Radar Imaging Satellite |
| RS | Remote Sensing |
| SAR | Synthetic Aperture Radar |
| SAVI | Soil Adjusted Vegetation Index |
| SIF | Sun Induced Fluorescence |
| SPAD | Soil Plant Analysis Development |
| SPOT | Système Pour l’Observation de la Terre |
| SWIR | Shortwave Infrared Region |
| TIR | Thermal Infrared |
| TM | Thematic Mapper |
| TRS | Thermal Remote Sensing |
| UAV | Unmanned Aerial Vehicles |
| UN | United Nation |
| USGS | United States Geological Survey |
| VRT | Variable Rate Technology |

## 1.1 Introduction

For about 2.5 million years, human species fed themselves by hunting animals and gathering plants. Human ecological footprint was minimal. Nearly about 10,000 years ago, human started controlling and manipulating few animals and plants species for their benefit. This leads to development of agrarian society with concept of advance food security. It translated into population explosion and more tilling for the extra food. Since then humans have been facing this cyclic phenomenon and surprisingly surviving it. But in the present scenario, horizontal expansion of agricultural activities is limited. Hence, our sole effort has been directed toward vertical expansion under limited resources.

The latest United Nations (UN) projections reveal that the world population will rise from 6.8 billion to 9.1 billion in 2050, which leads to an increase in demand for agricultural produces by 60% (Alexandratos and Bruinsma 2012). Other constraints like fragmented land holdings, land degradation, deterioration of soil health, the declining trend of the total crop productivity, as well as global climatic variations have posed serious threats in agricultural growth and development. However, to meet up with the future challenges to feed the 9 billion people of the world, there is a need to halt the declining trend of the total crop productivity, minimizing the rate of degradation of natural resources, and enhancing farm incomes through sustainable resources development plan. The adoption of newly emerged technology and tools like remote sensing (RS), geographic information System (GIS), global positioning system (GPS) and information technology (IT) might play a major role to enhance agricultural productivity in the future (Hakkim et al. 2016) through continuous monitoring and assessment of the natural resources. The gamut of all these technologies and tools, termed as geospatial technology, is a rapidly growing and changing field that assists the user in the collection, storage, analysis, interpretation, and dissemination of spatial data. It is a cost-effective approach which includes acquisition of real-time satellite images through RS, data analysis and management through GIS, location services and geo-referencing through GPS, and web services and outreach through IT. The advances in RS generate data for detailed inventory, mapping, and monitoring of crop, land, and water resources on a large scale (Gerhards et al. 2019). Satellite RS coupled with GIS and mobile app–based positional information has emerged as an efficient tool for the sustainable development in agriculture sector by optimizing input resources, minimizing the cost of production, and risk of biotic/abiotic in nature. Such technologies have the capabilities to provide “Decision Support Scenarios” which could be vital for monitoring the overall health of the agricultural sector and facilitate informed decision-making. Some of the major applications of geospatial technologies related to agriculture are crop inventory and monitoring (Schmedtmann and Campagnolo 2015; Ghazaryan et al. 2018; Heupel et al. 2018), crop growth simulation modeling, crop yield estimation (Huang et al. 2019; Ban et al. 2019; Phung et al. 2020), PA (Friedl 2018; Neupane and Guo 2019), soil mapping (Manchanda et al. 2002; Mulder et al. 2011), assessment of soil erosion (Woldemariam et al. 2018; Meena et al. 2018;

Zabihi et al. 2019); assessment of soil quality (Paz-Kagan et al. 2014, 2015), digital soil mapping (Ma et al. 2019; Wadoux et al. 2019), water management for irrigated agriculture (Taghvaeian et al. 2018; Tazekrit et al. 2018; Ojo and Ilunga 2018), agricultural land use planning (Ambika et al. 2016; Useya et al. 2019; Pareeth et al. 2019), etc. The medium and coarse resolution RS datasets can provide a regular and synoptic coverage of crop and soil resources at a continental or regional level. Whereas the fine-resolution satellite data helps in micro-level or farm-level agricultural activities such as water resources mapping, drainage pattern, management of fertilizers, pesticides, variable rate technology, crop insurance, crop damage assessment, etc. RS data of optical, microwave, thermal, and hyperspectral domain has proved to be a powerful tool to assess crop and soil properties in varying spatial and temporal scales. Several researchers (Mulla 2013; Pareeth et al. 2019; Rotairo et al. 2019; Phung et al. 2020) have shown the usefulness of RS technology to get spatially and temporally variable information for agriculture. A large number of satellite RS data are available nowadays to the researcher for natural resources management such as Moderate-Resolution Imaging Spectrometer (MODIS), Land Satellite (Landsat), Sentinel, Resourcesat-2, Cartosat-1, Cartosat-2, Planet, and QuickBird, etc. The number of satellite missions by various space agencies like National Aeronautics and Space Adminstration (NASA), European Space Agency (ESA), Japan Aerospace Exploration Agency (JAXA), China National Space Administration (CNSA), Indian Space Research Organization (ISRO), etc., dedicated to RS, has increased space resources sgnificantly over the past decades and will further increase over the coming decades and beyond. Nowadays several countries from the Asia-Pacific, South Asia, North America, and Europe are creating an Agricultural Market Information System which utilizes geospatial tools to fuse basic socioeconomic and crop statistics for the overall management of agriculture produce and demand–supply chain. In nutshell, geospatial technology has become part and parcel of agriculture management system. The technology has proven its potential and effectiveness, and also provides scope of future development.

## 1.2 Current Challenges in Agriculture: Global Perspective

Agriculture, in generic sense, is harvesting of sunlight toward conversion of carbon dioxide and water into carbohydrate/sugar. This basic translation is modulated by prevailing weather, pests and diseases, soil, and plant resources. Often agriculture is livelihood, not a profitable business, particularly in the third world countries. Hence, agriculture is done sub-optimally with limited resources in majority of the global arable land. This caters the biggest challenges as well as the opportunities of agriculture.

Feeding 9 billion of human population by 2050 is the target set by FAO (Alexandratos and Bruinsma 2012). It requires increase of agricultural produce by 60% from present status. The target is really challenging and further complicated by the changing global climatic pattern (Meena et al. 2018a). The world scientific community has reached to a broad consensus that the concentration of atmospheric greenhouse gases, mainly carbon dioxide, has been increasing unprecedently, and more so in the last few decades. This resulted in significant warming of global climate as evident from rise in global average air and ocean temperature, widespread melting of snow and ice, and rise in global average sea level. Studies across the globe have reported these changes over European region (Hasanean 2001; Domonkos and Tar 2003; Feidas et al. 2004), China (Liu et al. 2004), Japan and Korean peninsula (Chung and Yoon 2000; Yue and Hashino 2003), Malaysia (Tangang et al. 2007), Alaska (Stafford et al. 2000), and India (Revadekar et al. 2012; Chakraborty et al. 2017; Chakraborty et al. 2018). The warming pattern has also caused change in rainfall pattern, increase in extreme weather events, altered pest and disease profiles along with the crop phenology, and rapid degradation of land and soil quality (Cleland et al. 2007; Das et al. 2013; Chakraborty et al. 2014). The phenomena of the changing climatic and ecosystem condition have been found to be global in nature, though they do exhibit considerable spatial and temporal variability at local level.

To meet the demands of higher production, overexploitation of land may lead to land degradation. At present 33% of arable land suffers from various kinds of degradation processes. It is a global threat which leads to reduction in area and productivity of 13.4 billion ha of global cultivable land (Reddy 2003). Agricultural production is deleteriously affected due to inappropriate land care strategies in maximum portions of the world (Lambin and Meyfroidt 2011; Lambin et al. 2013). Sometimes direct impact of land degradation may appear in rapid desertification of semi-arid and arid region, frequent and intense drought occurrence, and loss of productive topsoil and biodiversity (Gibbs et al. 2010; Lambin and Meyfroidt 2011; Meena et al. 2020). Besides land degradation, volatile weather and extreme events would change the growing seasons; limit the availability of water; allow weeds, pests, and disease to thrive; and reduce crop productivity drastically. Apart from all the above-mentioned issues, some of the biggest problems facing the agricultural sector in developing and under-developed countries are low yield, fragmented land holdings, poor infrastructure, low use of appropriate and best farming techniques, a decline in soil fertility etc., which are leading contributors to low agricultural productivity. Hence, countries need to prioritize agriculture and growing food with more sustainable methods.

## 1.3 Importance of Geospatial Technologies

To meet up with the future challenges to feed the 9 billion people of the world, there is a need to continue investing in appropriate technologies to arrest the declining trend of the total crop productivity, minimizing the rate of degradation of natural resources, reducing environmental damage (including greenhouse gas emission), and enhancing farm incomes through a sustainable resources development plan. Over the few decades, the innovation in digital agricultural technologies such as precision farming (PF), crop monitoring and surveillance system, artificial intelligence (AI) in agricultural decision supports, IT-driven extensions are gaining more importance. The adoption of such newly emerged technology and tools into the entire agriculture value chain might play major role in increasing agricultural productivity in the future (Hakkim et al. 2016; Mitran et al. 2018a). These technologies help in continuous monitoring and assessment of the condition and availability of the agricultural resources and simultaneously transformed agriculture into a sustainable ecosystem. Further, it can also reduce the impact of agriculture on the global environment by optimizing the use of water, fertilizer, fossil fuel, and land for food production. The greenhouse gas emissions contributed by agriculture can also be mitigated through adopting climate-smart practices.

## 1.4 Geospatial Tools and Techniques

The modern geospatial technologies include RS, GIS, GPS, proximal sensing, mobile technology, etc., which can be used efficiently for agricultural resources management and precision farming. The overall idea and integration of such technologies are presented in Fig. 1.1.

### *1.4.1 Remote Sensing*

RS is the "science of making inferences about material objects from measurements, made at distance, without coming into physical contact with the objects under study" (Lillesand et al. 2015). A RS system consists of a platform (satellite, rocket, balloon, etc.), where a sensor can be mounted to collect and or emit radiation/signal (Sabins 1997). RS can be "active" when a signal is emitted by a satellite and its reflection by the object is detected by the sensor and "passive" when the object is illuminated by sunlight and its reflection/emission is detected by the sensor (Ran et al. 2017a, b). RS imagery along with GIS to process, alter, manipulate, store, and retrieve can very effectively used for natural resource management. RS images can be obtained either from sensor in satellite platform or boarded on small aircraft as aerial photography (Mulla 2013). Aerial photography is the original form of RS and remains the most widely used method until recently. It has few advantages, that is, aerial images are generally of high resolution depending on the flight height (3–5 km). They are relatively immune to the cloudiness, and acquiring time of the image can be scheduled at will. Aerial photographs are different types such as black and white, high- or low-altitude photographs, vertical/oblique, infrared, multi-spectral, etc. The selection of aerial photographs depends on the purpose of the study. These photographs are very useful in small areas for micro-level investigation. Vertical aerial photographs are mostly used in land use planning, cartography, specifically in photogrammetric surveys, to generate topographic maps (Twiss et al. 2001). Oblique

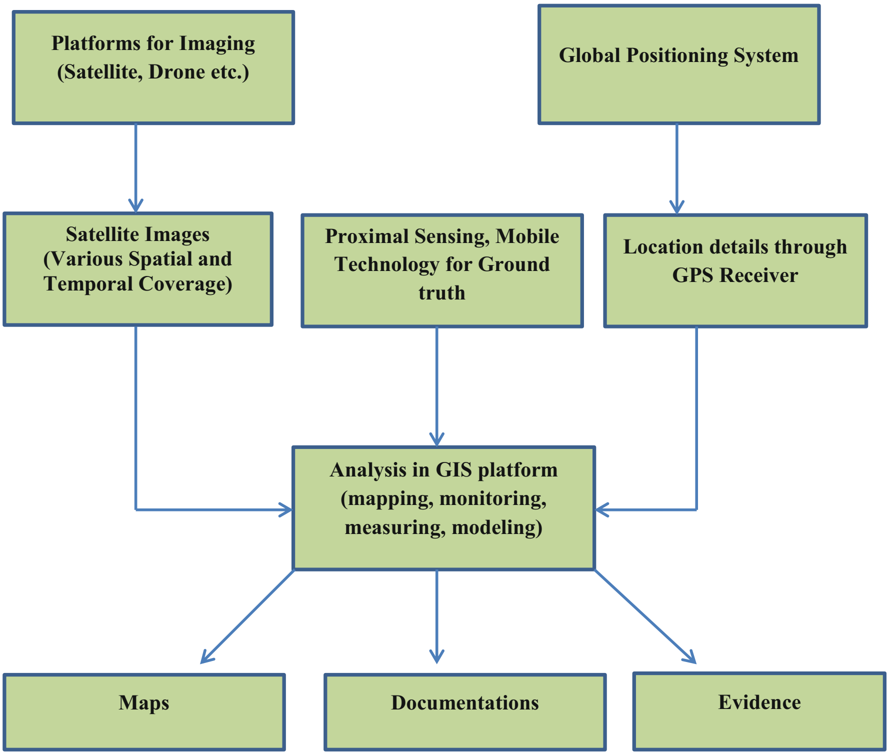


**Fig. 1.1** A schematic diagram on geospatial technologies

aerial photography is useful for environmental studies (Stewart et al. 2014). The satellite RS for systematic natural resources management began with the launch of the Earth Resources Technology Satellite (ERTS-1) by the USA in 1972, later renamed as LANDSAT. Remote sensors, such as on-board radiometers or spectro-radiometers allows the observation of large areas of the Earth surface (synoptic capability) at different wavelengths (optical, infrared, thermal, etc.) of the electro-magnetic (EM) radiation (multispectral capability) and at a frequent time interval (multi-temporal capability). Optical RS deals with collecting radiation reflected and emitted from the object under study within the EM spectrum of visible (0.4 μm), near-infrared (NIR) and thermal infrared (TIR, 15 μm). Landsat, Sentinel-2, Resourcesat, Quickbird, and SPOT satellites are the well-known multispectral satellite sensors. Optical RS is one of the suitable technologies for the analysis, surveying, mapping, and monitoring of soils and crops. However, using optical RS datasets for mapping have several limitations. Instrument calibration, atmospheric correction, and cloud screening for data especially during the monsoon period are major limitations for optical RS. However, the introduction of microwave remote sensing (MRS) overcame few issues such as monitoring the Earth's surface, irrespective of day/night and even in cloudy weather conditions which make it more effective and useful (Navalgund et al. 2007). The main advantages of MRS are its ability to penetrate the clouds, rain, vegetation, and even very dry soil surfaces. EM waves having frequencies between 109 and 1012 Hz are generally considered as microwaves. Radar is an active MRS system in which the terrain is illuminated using EM energy and the scattered energy returning from the terrain (known as radar return or backscatter) is detected and recorded as images. Examples of radar RS instruments include Synthetic Aperture Radar (SAR), scatterometers, altimeters, and radar sounders. MRS technology is been widely used for crop monitoring during the rainy season, soil moisture estimation, and land cover analysis. Sentinel-1, Radarsat-1&2, Radar Imaging Satellite (RISAT-1), Environmental Satellite (ENVISAT), Advance Land Observing Satellite–Phased Array type L-band Synthetic Aperture Radar (ALOS-PALSAR) are the well-known satellite sensors that use microwave sensors. Nowadays hyperspectral remote sensing is gaining more importance because of choice for more bands (>200 bands) as compared to multispectral imagery (between 3 and 10 bands). Hyperspectral imaging sensors measures surface reflectance with a given spatial resolution, covering an area instead of a single point (Gerighausen et al. 2012) and providing spectral information at high spatial density (Franceschini et al. 2015). Hyperspectral datasets have a greater potential to detect differences among land and water features. For example, multispectral imagery can be used to map cropped areas, while hyperspectral imagery can be used to map crop type too. The growing demand for large-scale investigations related to natural resources management and environmental issues has required the development of air- and spaceborne imaging spectroscopy. Currently, airborne hyperspectral sensors predominate over spaceborne imaging spectroscopy (Transon et al. 2018). Airborne sensors such as Airborne Visible Infrared Imaging Spectrometer (AVIRIS), DLR Earth Sensing Imaging Spectrometer (DESIS), and Airborne PRISM Experiment (APEX) have excellent potential for imaging spectroscopy (Rast and Painter 2019). Airborne hyperspectral data has been widely used for crops and soil assessment such as discrimination of crop type, retrieval of crop biophysical parameters, determination of soil mineral content, organic matter, nitrogen, salinity status, iron oxide content, and carbonate by using diagnostic absorption features of hyperspectral bands. Upcoming spaceborne sensors with high revisit time (from 3 to 5 days), higher spatial resolution, from several countries, are planned for launch in the coming years.

Besides hyperspectral RS, thermal remote sensing (TRS) is also gaining importance for natural resources and environmental studies. Thermal infrared radiation refers to EM waves with a wavelength of between 3 and 20 μm. Most of the TRS applications make use of 3–5 and 8–14 μm ranges. The major difference between the near infrared and thermal infrared is that NIR is the reflected energy where thermal infrared is emitted energy. The principle of TRS in agriculture is based on the emission of radiation responding to the temperature of the leaf and canopy. However, the emission of radiation varies with air temperature and the rate of evapotranspiration (Maes and Steppe 2012; Gerhards et al. 2019). TRS is widely used for the detection of plant responses to environmental and water stresses (Gago et al. 2015; Ramoelo et al. 2015; Khanal et al. 2017; Huang et al. 2018).

RS technology has a great potential to acquire high spatial, spectral, and temporal resolution data as input for PA (Gerhards et al. 2019). The advances in RS technology generate data for detailed inventory, mapping, and monitoring of crop, land, and water resources on large scale (Gerhards et al. 2019). A RS data user should be aware of various data products and their use in respective domains in order to choose a dataset. A variety of remote sensing satellite datasets with their specifications is distributed through different websites from manufacturers, satellite operators, data providers, and is presented in Table 1.1.

### *1.4.2 Proximal Sensing*

Besides remote sensing, proximal sensing is also getting attention in agriculture especially in precession farming. To overcome the constraints of satellite-based remote sensing, modern world is emphasizing on the use of proximal sensing techniques in PA to assess the growth and stress of crops. In proximal sensing, the platforms are mostly handheld, tractor based, stationary installation, and robotics managed, etc., and the sensors are in close contact to the object. The types of sensors used in this case can be simple RGB or gray-level imaging, multispectral, hyperspectral imaging, or IR-thermography (Rossel and Behrens 2010; Mulla 2013). Apart from reflectance, transmittance, and absorption, plant leaves can also emit energy by fluorescence (Apostol et al. 2003) or thermal emission (Cohen et al. 2005). Sensors have significant uses in the field of agriculture, especially in the field of plant monitoring. The information collected through the proximal and remote sensors is always tied to efficient data analysis approaches such as advance machine learning, data mining, spectral soil, and vegetation indices–based algorithms, identification of specific wavelength and feature, etc. The proximal RS is able to provide information on both biotic and abiotic stresses such as nutrient deficiency, pests, and diseases, etc. A number of proximal sensors such as Soil Plant Analysis Development (SPAD) meter (Schepers et al. 1992), green seeker (Raun et al. 2002), crop spec (Reusch et al. 2010), H-sensor artificial intelligence (Partel et al. 2019), etc. have been developed for crop assessment. Besides crop sensors, proximal soil sensors are also getting more attention in precision farming. Proximal soil sensors allow inexpensive and rapid collection of quantitative, precise, high-resolution data, which can be used to better understand soil temporal and spatial variability. Rossel et al. (2011) provided description of proximal soil sensing techniques used and the soil properties that can be measured by these technologies. The characterization of the temporal and spatial variation of soil at field and landscape level using point-based observation is time-consuming, expensive, and impractical. The remotely sensed satellite images, as well as aerial photos, can provide excellent spatial coverage; however, the measurement is, indirect, involves large uncertainties and typically limited to the surface to surface soil (5–6 cm), hence not appropriate to measure spatial and temporal variability at farm level. Such limitations make the proximal soils sensing increasingly popular by filling the data gap between the lower

**Table 1.1** The list of major satellite data available for agricultural and land resources assessment

| Satellite data | Spatial resolution | Temporal resolution (days) | Spectral coverage | Date range of acquisition | Provider/developer | Uses | Source |
|---|---|---|---|---|---|---|---|
| Landsat 7 ETM+ | 15, 30, 60 m | 16 | Band 1: 450–515 nm (30 m), Band 2: 525–605 nm (30 m), Band 3: 630–690 nm (30 m), Band 4: 750–900 nm (30 m), Band 5: 1550–1750 nm (30 m), Band 6: 1040–1250 nm (60 m), Band 7: 2090–2350 nm (30 m), Band 8: 520–900 nm (15 m) | Since April 15, 1999 | NASA/USGS | Vegetation types, crop classification, crop stress, crop water use, crop residue, land surface phenology, biomass content, water resources assessment, land use and land cover, land degradation, soil map, etc. | https://www.usgs.gov/land-resources/nli/landsat |
| ASTER | 15–90 m | 4–16 | Band 1: 520–600 nm (15 m), Band 2: 630–690 nm (15 m), Band 3: 760–860 nm (15 m), Band 4: 760–860 nm (15 m), Band 5: 1600–1700 nm (30 m), Band 6: 2145–2185 nm (30 m), Band 7: 2185–2225 nm (30 m), Band 8: 2235–2285 nm (30 m), | Since December 18, 1999 | NASA, USA<br>Government of Japan | Vegetation, ecosystem dynamics, crop stress, change detection, Earth science, land cover analysis, etc. | https://asterweb.jpl.nasa.gov/eos.asp |

(continued)

**Table 1.1** (continued)

| Satellite data | Spatial resolution | Temporal resolution (days) | Spectral coverage | Date range of acquisition | Provider/ developer | Uses | Source |
|---|---|---|---|---|---|---|---|
| | | | Band 9: 2295–2365 nm (30 m), Band 10: 2360–2430 nm (30 m), Band 11: 8125–8475 nm (90 m), Band 12: 8475–8825 nm (90 m), Band 13: 8925–9275 nm (90 m), Band 14: 10250–10,950 nm (90 m), Band 15: 10950–11,650 nm (90 m) | | | | |
| ASTER GDEM Version 3 | 30 m | | Created by compiling VNIR images | Version 3: August 2019 | METI, Govt. of JAPAN and NASA, USA | Elevation, slope, terrain analysis, topographic analysis, watershed management, land suitability, soil erosion, cartographic applications | https://asterweb.jpl.nasa.gov/eos.asp |
| MODIS | 250 m (B1-B2) | 1–2 | Band 1: 620–670 nm, Band 2: 841–876 nm Band 3: 459–479 nm; Band 4: 545–565 nm, Band 5: | Terra: December 18, 1999 | NASA | Land boundaries and properties, vegetation types, agricultural crop monitoring, | https://modis.gsfc.nasa.gov/ |
| | 500 m (B3-B7) | | | Aqua: May 4, 2002 | | | |
| | 1000 m (B8-B36) | | | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1230–1250 nm, Band 6: 1628–1652 nm, Band 7: 2105–2155 nm, Band 8: 405–420 nm, Band 9: 438–448 nm, Band 10: 483–493 nm, Band 11: 526–536 nm, Band 12: 546–556 nm, Band 13: 662–672 nm, Band 14: 673–683 nm, B15: 743–753 nm, Band 16: 862–877 nm, Band 17: 890–920 nm, Band 18: 931–941 nm, Band 19: 915–965 nm, Band 20: 3660–3840 nm, Band 21: 3929–3989 nm, Band 22: 3.929–3.989 nm, Band 23: 4020–4080 nm, Band 24: 4433–4498 nm, Band 25: 4482–4549 nm, Band 26: 1360–1390 nm, Band 27: 6535–6895 nm, Band 28: 7175–7475 nm, Band 29: 8400–8700 nm, Band 30: 9580–9880 nm, Band | | | drought assessment, regional crop stress, vegetation phenology, crop residues, land use and land cover, long-term changes, primary productivity, ecosystem fluxes, Crop biophysical parameter, evapotranspiration, forest fire, global climate change, atmospheric correction, aerosol, ice and snow study, snow melt run-off, etc. | |

(continued)

**Table 1.1** (continued)

| Satellite data | Spatial resolution | Temporal resolution (days) | Spectral coverage | Date range of acquisition | Provider/ developer | Uses | Source |
|---|---|---|---|---|---|---|---|
| | | | 31: 10780–11,280 nm, Band 32: 11770–12,270 nm, Band 33: 13185–13,485 nm, Band 34: 13485–13,785 nm, Band 35: 13785–14,085 nm, Band 36: 14085–14,385 nm | | | | |
| Landsat 8<br>OLI (B1-B9)<br>TIRS (B10-B11) | 15, 30, 60, 100 m | 16 | Band 1: 433–453 nm (30 m), Band 2: 450–515 nm (30 m), Band 3: 525–600 nm (30 m), Band 4: 630–680 nm (30 m), Band 5: 845–885 nm (30 m), Band 6: 1560–1660 nm (60 m), Band 7: 2100–2300 nm (30 m), Band 8: 500–680 nm (15 m), Band 9: 1360–1390 nm (30 m), Band 10: 1060–1120 nm (100 m) (IR), Band 11: | Since February 11, 2013 | NASA/USGS | Vegetation types, crop classification, crop stress, crop water use, crop residue, land surface phenology, vegetation biomass content, water resources assessment, land use and land cover, land degradation, soil map, etc. | https://www.usgs.gov/land-resources/nli/landsat |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | 1150–1250 nm (100 m) (IR) | | | | |
| ResourceSat | AWiFS: 56 m | AWiFS: 2–3; LISS-III: 12–13; LISS-IV:25–26 | AWiFS: 56 m (ResourceSat 1, ResourceSat 2, 2A) | ResourceSat-1 October 17, 2003, ResourceSat-2 April 20, 2011, ResourceSat- 2A December 7, 2016, | ISRO | Crop monitoring, crop classification, drought monitoring, horticulture, water resource assessment, land use land cover, soil map, wasteland mapping, land degradation, etc. | https://www.isro.gov.in |
| | LISS-III:23.5 m | | Band 2: 520–590 nm | | | | |
| | LISS-IV:5.8 m | | Band 3: 620–680 nm | | | | |
| | | | Band 4: 770–860 nm | | | | |
| | | | Band 5: 1,550–1700 nm | | | | |
| | | | LISS-III:23.5 m (ResourceSat 1, ResourceSat 2, 2A) | | | | |
| | | | Band 2: 520–590 nm | | | | |
| | | | Band 3: 620–680 nm | | | | |
| | | | Band 4: 770–860 nm | | | | |
| | | | Band 5: 1,550–1700 nm | | | | |
| | | | LISS-IV:5.8 m 1 (mono), 3 (MX) (ResourceSat 2, 2A) | | | | |
| | | | Band 2: 520–590 nm | | | | |
| | | | Band 3: 620–680 nm | | | | |
| | | | Band 4: 770–860 nm | | | | |
| Sentinel 2 | 10, 20 or 60 m | 5 | Band 1: 421–457 nm (60 m), Band 2: 439–535 nm (10 m), Band 3: 537–582 nm | Sentinel 2A: 2015.<br>Sentinel 2B in 2017. | ESA | Vegetation types, crop classification, crop stress, crop water use, crop | https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-2 |

(continued)

**Table 1.1** (continued)

| Satellite data | Spatial resolution | Temporal resolution (days) | Spectral coverage | Date range of acquisition | Provider/ developer | Uses | Source |
|---|---|---|---|---|---|---|---|
| | | | (10 m), Band 4: 646–685 nm (10 m), Band 5: 694–714 nm (20 m), Band 6: 731–749 nm (20 m), Band 7: 768–796 µm (20 m), Band 8: 767–908 nm (10 m), Band 8a: 848–881 nm (20 m), Band 9: 931–958 nm (60 m), Band 10: 1338–1414 nm (60 m), Band 11: 1539–1681 nm (20 m), Band 12: 2072–2312 nm (20 m) | | | residue, land surface phenology, vegetation biomass content, water resources assessment, land use and land cover, land degradation, soil map, etc. | |
| WorldView-2 | 0.5 m and 1.84 m | 1.1 | Pan: 450–800 nm | October 8, 2009 | Digital Globe, USA | Farm level crop monitoring, crop damage assessment, crop parameter retrieval, precision farming, crop insurance, micro-watershed assessment, farm asset mapping, | https://spacedata.copernicus.eu/web/cscda/missions/worldview-2 |
| | | | Coastal: 400–450 nm | | | | |
| | | | B: 450–510 nm | | | | |
| | | | G: 510–580 nm | | | | |
| | | | Y: 585–625 nm | | | | |
| | | | R: 630–690 nm | | | | |
| | | | Red Edge: 705–745 nm | | | | |
| | | | NIR 1: 770–895 nm | | | | |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | NIR 2: 860–1040 nm | | | horticulture, irrigation infrastructure, etc. | |
| Rapid Eye | 6.5 m | 5.5 | B: 440–510 nm<br>G: 520–590 nm<br>R: 630–680 nm<br>Red Edge: 690–730 nm<br>NIR: 760 – 850 nm | August 29, 2008 | Rapid Eye AG, Germany | Farm-level crop monitoring, crop damage assessment, crop parameter retrieval, precision farming, crop insurance, micro-watershed assessment, farm asset mapping, horticulture, irrigation infrastructure, etc. | https://earth.esa.int//web/guest/missions/3rd-party-missions/current-missions/rapideye |
| Ikonos | 80 cm B/W<br>3.2 m RBGiR | 1–3 | B/W: 445–900 nm, B: 445–516 nm, G: 506–595 nm, R: 632–698 nm, NIR: 757–853 nm | Launch September 24, 1999 | Digital Globe, USA | Farm-level crop monitoring, crop damage assessment, crop parameter retrieval, Precision farming, crop insurance, micro-watershed assessment, farm asset mapping, | https://directory.eoportal.org/web/eoportal/satellite-missions/i/ikonos-2 |

(continued)

**Table 1.1** (continued)

| Satellite data | Spatial resolution | Temporal resolution (days) | Spectral coverage | Date range of acquisition | Provider/ developer | Uses | Source |
|---|---|---|---|---|---|---|---|
| | | | | | | horticulture, irrigation infrastructure, etc. | |
| SPOT | Spot 6, 7: | 1–4 | B/W: 455–745 nm, R: 625–695 nm, G: 530–590 nm, B: 450–520 nm, NIR: 760–890 nm | SPOT 6: September 9, 2012; SPOT 7: June 30, 2014 | Centre national d'études spatiales (CNES), SSTC and Swedish National Space Board | Crop monitoring, crop classification, drought monitoring, horticulture, water resource assessment, land use, land cover, soil map, wasteland mapping, land degradation, etc. | https://earth.esa.int/web/guest/data-access/browse-data-products/-/article/spot-6-and-7-archive-and-new |
| | Panchromatic – 1.5 m | | | | | | |
| | Multispectral – 6.0 m (B,G,R, NIR) | | | | | | |
| Cartosat | Cartosat-1: 2.5 m | 5 | Cartosat-1, 2 and 2A: panchromatic band (500–850 nm) | CartoSat-1: May 5, 2005, CartoSat 2–2: January 10, 2007, CartoSat-2A: April 28, 2008. | ISRO | Cartographic applications, rural applications, coastal land use, creation of land use maps, precision farming, horticulture, farm asset mapping, encroachment, etc. | https://www.isro.gov.in |
| | Cartosat-2 and 2A: 0.8 m | | | | | | |
| CartoDEM | 10 m | | Cartosat-1 stereo data | May 5, 2005 | ISRO | Elevation, slope, terrain analysis, topographic analysis, cartographic | https://www.isro.gov.in |

| | | | | | | | |
|---|---|---|---|---|---|---|---|
| | | | | | | applications, quantitative analysis of run-off and soil erosion, etc. | |
| KOMPSAT (Korea Multiple-Purpose Satellite) | KOMPSAT-3: 0.70 m | 1.4 | KOMPSAT 3: PAN: 450–900 nm, MS1 (Blue): 450–520 nm, MS2 (Green): 520–600 nm, MS3 (Red): 630–690 nm, MS4 (NIR): 760–900 nm | KOMPSAT 3: May 17, 2012; | Korea Aerospace Research Institute (KARI) | Farm-level crop monitoring, crop damage assessment, crop parameter retrieval, precision farming, crop insurance, micro-watershed assessment, farm asset mapping, horticulture, irrigation infrastructure, etc. | https://spacedata.copernicus.eu/web/cscda/missions/kompsat-3 |
| | KOMPSAT-3A:0.55 m | | KOMPSAT 3A: same as KOMPSAT 3 with MWIR: 3300–5200 nm | KOMPSAT 3A: March 25, 2015 | | | |
| Sentinel 1 | Strip Map: 5*5 m; | 6–12 | C-band synthetic-aperture radar (5.405 GHz) | Sentinel-1A: April 3, 2014, | ESA | Agricultural monitoring, soil moisture assessment etc., soil erosion studies | https://sentinels.copernicus.eu/web/sentinel/missions/sentinel-1 |
| | Interferometric Wide:5*20; Extra Wide Swath:25*100; | | | Sentinel-1B: April 25, 2016 | | | |
| | Wave (WV) Mode:5*20 | | | | | | |
| RADARSAT | 8–100 m | 3 | Synthetic Aperture Radar (SAR) | RADARSAT 1 launched on November 4, 1995. | Canadian Space Agency | Hydrology, agricultural monitoring, soil moisture, rice crop mapping, crop biophysical parameters, etc. | www.asc-csa.gc.ca/eng/satellites/radarsat |
| | 3 × 1 m–100 × 100 m | | RADARSAT 1 and 2: C-band (5.6 cm) | RADARSAT 2 launched on December 14, 2007 | | | |

(continued)

**Table 1.1** (continued)

| Satellite data | Spatial resolution | Temporal resolution (days) | Spectral coverage | Date range of acquisition | Provider/ developer | Uses | Source |
|---|---|---|---|---|---|---|---|
| RISAT | RISAT 2: 50 m RISAT 1: 1 m, | RISAT-1: 25 | RISAT 2: X-band SAR | RISAT 2: April 20, 2009 | ISRO | Surface topography and costal change; land use monitoring, agricultural monitoring, rice crop mapping, etc. | https://www.isro.gov.in |
| | RISAT 2B: 0.5*0.3 m | RISAT 2 and 2B: 3 to 4 | RISAT 1: C-band SAR (5.35 GHz) | RISAT 1: April 26, 2012, | | | |
| | | | RISAT 2B: X Band | RISAT-2B: May 22, 2019 | | | |
| ALOS-PALSAR 2 | Stripmap:3,6 and 10 m | 14 | L band SAR (1.2 GHz) | May 24, 2014 | JAXA | Cartographic applications, environmental monitoring | https://www.jaxa.jp/projects/sat/alos2/index_j.html |
| | ScanSAR: 60 and 100 m | | | | | | |
| EO 1 Hyperion | 30 m | 16 | 422–2395 nm | November 21, 2000; Deactivated on March 30, 2017 | NASA/GSFC | Crop monitoring, crop condition, crop pest and disease assessment, crop nutrient stress, soil mapping, land degradation assessment, etc. | https://archive.usgs.gov/archive/sites/eo1.usgs.gov/index.html |
| HJ-A/HSI | 100 m | – | 450–950 nm | September 5, 2008 | Academy of Space Technology China | Agriculture, crop assessment, land classification, monitoring, soil salinity assessment, etc. | www.cresda.com |
| SRTMShuttle Radar Topography Mission | 30 and 90 m | – | X band: 3.1 cm | February 11, 2000 | NASA | Elevation, slope, terrain analysis, topographic analysis, cartographic applications | https://www2.jpl.nasa.gov/srtm/ |
| | | | C band: 5.6 cm | | | | |

resolution remotely sensed data and high-resolution point data (Adamchuk 2011; Rossel et al. 2011). A number of the proximal sensors as well as methods such as ground-penetrating radar, EM induction, electrical resistivity, magnetometry, optical reflectance, gamma-ray spectroscopy, etc., have been used for farm- and landscape-level soil survey to indirectly measure the spatial and temporal variability of soil properties. Various soil physical and chemical properties such as soil texture, porosity, pH, bulk density, soil structure, salinity, organic carbon, moisture content, $CaCO_3$ content, cation-exchange capacity, ionic composition, plant-available nutrients, as well as metal content in contaminated soil, etc. can be assessed using various proximal soil sensing methods (Doolittle and Brevik 2014; Dao 2018).

### *1.4.3 Geographic Information System*

GIS is a computerized system for gathering information of Earth features with a geographic reference system (latitude, longitude, coordinates, projection). Visual representation either through map generation or any other digital image format makes it a unique one to the users. It is a blend of computer technology and mapping science of geography – regarded as computational geography (Kavita and Patil 2011). Many other terms synonymously used in place of GIS include spatial data handling system (Marble and Peuquet 1983), geographic data system (White 1984), spatial information system, geo-data system, geo-based information system, natural resource information system (Clarke 1986), multipurpose cadastre, etc. The basic functions of GIS are collection of Earth's information, analysis, update, manipulation, storage, complex relation and integration of data, interpretation and visual representation for further decision-making through a systematic way integrating personnel, institutions, hardware, data, and software (Supuwiningsih and Rusli 2017). What GIS does is basically capturing location-specific information and its facile displaying to the user for better understanding, interpretation, and informed decision-making.

GIS is an assemblage of computer hardware, software, storage device, modeling or logical interface, operating personnel, and geographic information collected through capturing device or remotely sensed tools (Chang et al. 2009; Pendleton 2012). GIS is dished out into two major groups (Gangwar 2013):

(i) Base data or core data or framework data (common for all applications): Data includes information about elevation, natural or constructed features of the Earth's surface, geodetic frameworks for navigation, etc.
(ii) Thematic data (application-specific data): This data varies according to the user's application, for example, socioeconomic data from planning and censuses, natural resource data, or modified forms of base data, etc.

GIS contains a database management system to handle two types of data: spatial (real-world geo-referenced information) and attribute data (a characteristic feature of objects). It undergoes spatial analysis to find out trends, patterns, shapes, and relationships of data. Spatial analysis is of different types like overlay analysis (superimposing thematic layers to go insight of the data), proximity analysis (to find out how much features are close to each other), buffer analysis (this is a type of proximity analysis which is determined through distance around features and applied to points, lines, or polygons to discover areas in or outside the buffer area) (Farkas et al. 2016), etc. GIS incorporates only two kinds of data, namely vector- and raster-featured data. Vector and raster featured data describe discrete and continuous features, respectively. Vector-featured data comprises point (no dimension), line (one dimension), and area or polygon (two dimensions), while raster-featured data includes grid cells and pixels (Wieczorek and Delmerico 2009). Point is displayed on screen or maps by reducing its scale as a symbol. For example, the corner of a building is shown by a point as a representative of coordinates. Line, on the other hand, connects two points and thus represents one dimension. For instance, the boundary of a water body can be marked by a line. The area, as well as polygon, represents two-dimensional specifications (community land or water body or vegetation land uses) by incorporating at least three connecting lines through different points (Chang et al. 2009). Polygons have an area and perimeter values and are used to represent a wide range of physical (types of soil, forests, and water bodies), anthropogenic (land parcels, administrative boundaries), and other features (Sugumaran and DeGroote 2011). In raster GIS, a unique reference coordinate or cell address represents discrete attribute data contained a grid cell or pixel at a corner or center. Raster format superimposes imageries over grid cells for better features' identification, and pixel size or grid decides the resolution of images. Unlike vector format, raster GIS undergoes scalar operations on spatially explicit data and requires conversion into vector format before further operations. Nowadays, many GIS software like ArcGIS, QGIS, Maptitude, GeoMedia, etc. can easily transform those formats into each other. GIS provides data output and presentation through charts and maps as these communicate better than words. Chart expresses the tabular data in some graphical diagrams like area, bar, column, line, scatter, and pie. GIS-based software has dynamic charts for automatic updating. On another side, maps like planimetric, topographic, cadastral, image, thematic, etc. represent features related to Earth through pictorial or symbolized formats embodied by scales, coordinates, etc. A list of GIS software used for spatial data analysis is presented in Table 1.2.

### *1.4.4 Global Positioning System*

GPS is a satellite-based navigation system, capable of locating any positions on the Earth. It can supply real-time, three-dimensional data regarding positions, navigation, and timing continuously 24 h/day. The development of GPS was primarily

**Table 1.2** A list of GIS software for spatial data analysis

| GIS software | Developer | Country | References |
|---|---|---|---|
| ArcGIS | Environmental Systems Research Institute (ESRI) | Redlands, California, USA | https://www.esri.com/en-us/arcgis |
| GeoMedia (Hexagon) | Intergraph | Madison, Alabama, United States | https://geospatial.intergraph.com/products/GeoMedia |
| QGIS | Open Source Geospatial Foundation | Chicago, USA | https://qgis.org/en/site |
| SAGA-GIS | Department of Physical Geography, University of Gottingen, | Germany | https://www.saga-gis.org/en |
| GRASS GIS | GRASS Development Team | Chicago, USA | https://grass.osgeo.org/ |
| gvSIG | Open Source Geospatial Foundation | Chicago, USA | https://www.gvsig.org |
| ENVI | Harris Geospatial Solutions | Broomfield, Colorado, United States | https://www.harrisgeospatial.com |
| MapInfo Professional | Pitney Bowes | Stamford, Connecticut, USA | https://www.mapinfo.com |
| Global Mapper | Blue Marble Geographics | Hallowell, Maine, USA | https://www.bluemarblegeo.com/products/global-mapper.php |
| Manifold GIS | Manifold Software Limited | USA | https://www.manifold.net |
| Smallworld | GE Energy Connections | Cambridge, England | https://www.ge.com |
| Bentley Map | Bentley Systems, Incorporated | Exton, Pennsylvania, USA | https://www.bentley.com |
| MapViewer and Surfer | Golden Software LLC | Golden, Colorado, USA | https://www.goldensoftware.com |
| Maptitude | Caliper Corporation | Newton, Massachusetts, USA | https://www.caliper.com |
| SuperGIS | Supergeo Technologies | Taipei, Taiwan | https://www.supergeotek.com |
| Super Map | SuperMap Software Co., Ltd | Beijing, China | https://www.supermap.com |
| PCIGeomatica | PCI Geomatics | Markham, Ontario, Canada | https://www.pcigeomatics.com |
| IDRISI | Clark Laboratories | Worcester, MA USA | https://clarklabs.org |
| AutoCAD Map 3D | Autodesk | San Rafael, California, United States | https://autodesk.com |
| Tatuk GIS | TatukGISSp | Gdynia, Poland | https://www.tatukgis.com |
| MicroImages (TNTgis) | MicroImages, Inc | Lincoln, Nebraska, USA | https://www.microimages.com |

(continued)

**Table 1.2** (continued)

| GIS software | Developer | Country | References |
|---|---|---|---|
| MapMaker Pro (MapMaker) | Map Maker Limited | Argyll, Scotland, UK | https://www.mapmaker.com |
| MapRite | Envitia | Reston, VA, USA | https://www.envitia.com |
| Ilwis | 52°North ILWIS Community | Netherlands | https://www.52north.org |

made for military applications and it started mainly as a Navigation System with Time and Ranging Global Positioning System (NAVSTAR GPS), but it was made available for civilian use since the 1980s. There are at least 24 GPS satellites in action for all the times which synchronize operations so that these repeated signals are transmitted at the same instance. It can calculate its position in three dimensional space when the receiver estimates the distance to at least four GPS satellites also referred to as trilateration. Most of the handheld GPS have 20 m positional and 1 m location accuracy. However, submeter location accuracy could also be obtained by using Differential GPS (DGPS). There are no subscriptions or setup charges required to use GPS. Hence, it can be accessed by anyone for any application which needs location coordinates. This has opened many new avenues for spatial data analyses. Nowadays farmers could access the GPS to perform site-specific farm activities. In GPS, several satellites are involved in the identification of the actual position of farm equipment within the field. GPS is a real-time, accurate, all-weather, economic, and continuously available positioning system. Hence, it has emerged as a unique surveying technique with wide range of applications in various domain. The major applications of GPS in agriculture are as follows:

I. Geophysical and cadastral surveys
II. Determination of the precise location in the field for spatial variability assessment
III. Determination of the precise location in the field for site-specific input applications
IV. Yield mapping
V. Integration of all field-based variables such as the intensity of weeds, crop yield, and soil moisture, etc. with RS data using DGPS
VI. Crop insurance value chain
VII. Agricultural supply chain
VIII. Disaster management and support

## 1.5 Role of Geospatial Technologies in Sustainable Agriculture

The discoveries in the field of science and technology during the twentieth and twenty-first centuries, especially geospatial technology, have enabled farmers to effectively use farm inputs to maximize crop yield. Geospatial technologies play a vital role in major agriculture application areas such as crop, soils, land, water, climate, and risk-related studies with data, models, and analytics. The geospatial technologies are playing a meaningful role in agriculture in the following ways:

(a) Easy and timely data acquisition
(b) Near real-time visualization and assessment of natural resources
(c) High-resolution and accurate mapping and assessment
(d) Optimize planning tools and techniques for agricultural activities (seeding, irrigation, fertilization etc.)
(e) Facilitate real-time mapping and monitoring of farm operations
(f) Improve yield and productivity of crops
(g) Centralized management of spatial and nonspatial data at farm level
(h) In-season crop damage assessment
(i) Support to the crop insurance value chain
(j) Easy dissemination of agricultural data through web
(k) Improving farm incomes while minimizing risk

There are various approaches to optimize agricultural activities through geospatial technologies such as climate-smart agriculture (CSA), precision farming (PF), conservation agriculture (CA), etc. Such approaches can optimize the use of farm inputs and resources which helps to reduce the cost of production and minimize agricultural risk and hazards, hence, improve the crop productivity and farm income. CSA coined by FAO is described as "agriculture that sustainably increases productivity, resilience (adaptation), reduces/removes greenhouse gases (GHGs) (mitigation), and enhances achievement of national food security and development goals". The adoption of CSA by farmers can improve crop production, increase economic growth, reduce greenhouse gas emission, create jobs, and hence decline hunger and poverty. PF is the use of geospatial tools and techniques to assess spatial and temporal variability associated with crop production factors to enhance crop performance and environmental quality (Pierce and Nowak 1999). It is also known as satellite agriculture, PF can relate to an agricultural production system with a robust set of technologies, including RS, GIS, GPS, and Variable Rate Technology (VRT) which can propel agriculture into the computerized information-based world. Nowadays geospatial technologies are playing a crucial role in CA. The real-time spatial and temporal satellite data analysis helps in the formulation of a series of land management practices that include soil management practices to reduce land degradation, introduce cover crops, retention of crop residues, recommended suitable cropping sequences, etc.

## 1.6 Crop and Soil Factors Influencing Remote Sensing

There are several crop and soil attributes that influence remote sensing signal. The amount of energy absorbed and transmitted by a plant leaf is affected principally by the amount and type of chlorophyll content, leaf internal structure, leaf water content, and leaf biomass content etc. It is further modulated by leaf area per unit land, leaf arrangement (leaf angle distribution), background soil reflectance, sun-sensor geometry at canopy level. Leaf-level synthetic spectral reflectance generated by PROSPECT-D model using different input parameters are presented in Fig. 1.2 (http://opticleaf.ipgp.fr/index.php?page=prospect). Among the plant pigments, chlorophyll-a and chlorophyll-b absorb radiation strongly in the visible wavelength range (400–700 nm) specifically 430 (blue) and 660 (red) nm for chlorophyll-a; and 450 (B) and 650 (R) nm for chlorophyll-b. Both chlorophyll-a and -b absorb light, but chlorophyll-a plays a dominant and critical role in converting light energy to chemical energy (Pinter et al. 2003). Due to the absorption of chlorophyll, the healthy green leaf shows very low reflectance values (~5–10%) in the blue and red region of the EM spectrum. The green region exhibits comparatively higher reflectance (~10–15%) making the plant leaf green in color. Sudden surge in reflectance is observed (~40–50%) in the near-infrared (700–1000 nm) due to well-developed leaf internal structure of spongy parenchyma and air space (Salama 2011). This is followed by two weak water absorption bands (970, 1200 nm) in

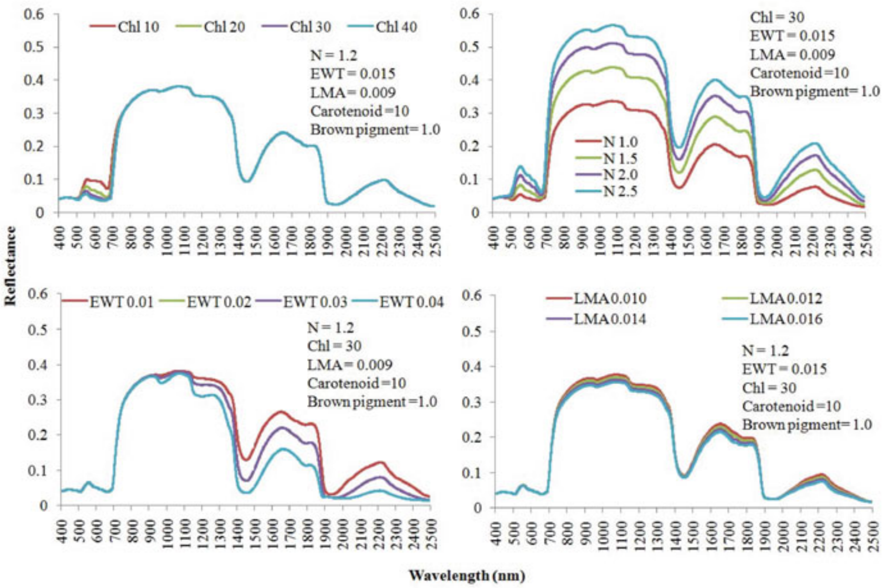


**Fig. 1.2** Spectral response vegetation as influenced by chlorophyll$_{a+b}$ content (Chl) in µg cm$^{-2}$, leaf structural parameters (N), equivalent water thickness (EWT) in cm, leaf mass per unit area (LMA) g cm$^{-2}$; carotenoid content in µg cm$^{-2}$, brown pigment (arbitrary unit)

NIR and two strong water absorption bands (1450, 1940 nm) in Shortwave Infrared Region (SWIR). The response of leaf reflectance spectra with the variation of the major inputs are presented in Fig. 1.2. Keeping other factors constant, the leaf chlorophyll content has been varied from 10 to 40 μg $cm^{-2}$ and the effect on the reflectance spectra is observed in the visible region only (400–700 nm). The absorption at blue and red bands has increased with the increase in the chlorophyll content. The reflectance at green region has also decreased as the higher chlorophyll content turn the leaf darker. The leaf internal structure (N) parameter is found to be highly sensitive. The N parameter has been increased from 1 to 2.5 keeping other inputs as constant, and the spectral reflectance is found to increase drastically. The effect was found across the spectral band but more pronounced in the reflection peaks than the absorption regions. The leaf wetness parameters, that is, Equivalent Water Thickness (EWT) is found to have effect on the NIR and SWIR of the spectrum. The spectral response with the increase of EWT from 0.01 to 0.04 cm, keeping other variables constant, is presented in Fig. 1.2. With the increase in EWT, the depth of the water absorption bands have increased. It has effectively brought down the whole spectra from NIR to SWIR proportionately. The effect of leaf mass per unit area (LMA) was found in NIR to SWIR with marginal effect. The reflectance is found to be marginally decreased with no change in the absorption region. As other parameters are kept constant, the increase in LMA made the leaf internal structure more compact with less airspace. This results in a decrease of reflectance in the NIR and SWIR regions, as depicted in Fig. 1.2. Please be informed that the driving parameters of leaf reflectance act simultaneously and produce a mix response in practical scenarios.

An interesting observation revealed that when a plant goes to the senescence stage, reflectance begins to downhill in the near-infrared region (collapse of leaf internal structure) and uphill in the red regions (loss of leaf chlorophyll). The absorption mechanism of EM radiation in the pigments of green vegetation is attributed to atomic excitation by photon, where the electron is bumped into higher energy orbital that lies further from the nucleus (Jensen et al. 2008; Salama 2011). On the contrary, a high value of plant reflectance in the near-infrared (NIR 700–1300 nm) region is an effect of leaf density and canopy arrangement. During the senescence stage, a relatively faster degradation of chlorophylls compared to carotenoids causes a significant increase in reflectance in the red wavelength. However, a low value of reflectance at the NIR region is due to collapsing of the spongy-mesophyll layer as the leaf comes under stress. In this decaying phase of the plant, carotenes absorb blue and reflect green and red, resulting in the yellow appearance of the leaves. Due to the death of brown pigments known as tannins, leaf reflectance and transmittance in 400–700 nm decrease (Fourty et al. 1996; Salama 2011). This distinct difference in reflectance behavior between the red and NIR portions of the spectrum is the stimulus for the generation of spectral indexes (Sripada et al. 2006). These indexes are very frequently used to assess various plant canopy attributes such as biomass, chlorophyll and moisture content, leaf area index (LAI), Nitrogen (N) content, etc.

The most important contributing soil factors are moisture and organic matter content which affect the amount of radiation reflected by bare soils. Reflection of radiation from bare soil is also affected by soil texture, $CaCO_3$, calcium, and iron oxides (Rossel et al. 2006). Each soil property has its own specific spectral region where reflectance is the strongest (Ben-Dor et al. 2007). In cultivated land, bare soil and crop canopies are often both present. The mixing of the spectral signatures from bare soil as well as crop canopies often confuses the interpretation of the reflectance data. A few techniques are available to isolate information about plant characteristics from the mixture of reflectance, which includes spectral indexes that adjust for soil effects (Haboudane et al. 2004), spectral unmixing algorithm (Huete and Escadafal 1991), and derivative spectra (Demetriades-Shah et al. 1990).

## 1.7 Application of Geospatial Technologies in Crop Science

During late twentieth and early twenty-first centuries, the applications of RS and GIS in crop science are gaining more attention through crop inventory/mapping and management. RS is capable of providing spatially explicit and efficient crop inventory (crop map, crop acreage estimation, crop production estimates etc.) and management (crop condition, crop damage, drought monitoring and assessment, precision farming, cropping system analysis, etc.) as it can capture information at wide ranges of spatial and temporal scales with wall-to-wall coverage (Liaghat and Balasundram 2010). Typical vegetation signature across the EM domain (400–2500 nm) is presented in Fig. 1.2. The leaf-level signature is principally governed by the leaf pigments, leaf water content, leaf biomass, and internal structures as discussed earlier. Hence, the crops having differences in these parameters produce unique signature of spectral reflectance. Further at the canopy level, the signature is modulated by the unique crop spacing, canopy architecture, background soil exposure, etc. The crop signature can also be separated using the temporal frame of the crop-growing season. Global- and regional-scale crop maps have been successfully generated with considerable accuracy using the aforementioned spectral and temporal signatures. This becomes the basis of successful monitoring and assessment of crop. The functionality of GIS enables integration of other thematic services like soil maps, weather maps, and other resources maps which facilitate rapid and reliable decision-making. The satellite remote sensing application in crop science begins with the classification of land cover types with major emphasis on crop types. However, nowadays the focus has been shifted more toward the characterization of plant biophysical parameter, yield prediction, and crop production forecasting. RS of agricultural has provided valuable insights into various agronomic parameters such as start of the season, end of the season, seasonal greenness, crop condition anomalies, crop damage, etc. One of the main advantages of RS techniques is considered to be repeated information retrieval without any destructive sampling of crops. The response of vegetation cover to different spectral bands varies depending on the change in physical and biological properties of the vegetation canopies of different crops. Hence, various multispectral, broadband vegetation indices such as Normalized Difference Vegetation Index (NDVI), Normalized Difference Red Edge Index (NDRI), Soil-Adjusted Vegetation Index (SAVI), etc. along with weather parameters derived from surface and satellite observations have been widely used for crop studies (Schmedtmann and Campagnolo 2015; Lira Melo de Oliveira Santos et al. 2019; Zortea and Rodrigues 2019). Nowadays the introduction of hyperspectral remote sensing enables researchers to a more detailed analysis of crops such as crop classification, crop condition, retrieval of crop biophysical and biochemical attributes, crop stress (Ennouri and Kallel 2019; Virnodkar et al. 2020), as well as disease and pest etc. (Bhattarai et al. 2019; Yones et al. 2019). Several researchers have developed narrow-band vegetation indices using hyperspectral information for analysis and monitoring of crops and retrieval of different biophysical and biochemical variables of a plant (Shelestov et al. 2017; Pasqualotto et al. 2019; Darvishzadeh et al. 2019). Accurate estimates of crop biophysical as well as biochemical variables like LAI, fraction of absorbed photosynthetically active radiation (FAPAR), leaf moisture and chlorophyll content, primary production, sun-induced fluorescence (SIF) from RS can assist in determining vegetation physiological status (Penuelas et al. 1995). The study of crop phenology and its seasonal dependence, and seasonal dependence (Belanger et al. 1995), may serve as bioindicators of vegetation stress (Zarco-Tejada et al. 2001), and are crucial for sustainable agriculture. The introduction of microwave data enables the researcher to assess crops mainly in the rainy season during kharif. The development in the field of satellite and sensor in the last few decades makes a remote sensing–based approach as the most trusted and efficient tool to pre-harvest crop production estimation. Geospatial tools along with various modeling approaches such as machine learning, principle component analysis, lambda–lambda models, stepwise discriminant analysis, artificial intelligence, pattern recognition, mobile computing, etc. have opened a new dimension in crop science (Thenkabail et al. 2004). Similarly, process-based crop growth simulation models using RS and GIS-based inputs have been proven potential tools for analyzing crop behavior and yield prediction in various spatial and temporal scales. Nowadays, the modern world is emphasizing on the use of proximal remote sensing techniques in PA to assess the growth and stress of crops. Besides, unmanned aerial vehicle (UAV) or drone is showing its potential in farm resource management by capturing quality images of various aspects of crop cultivation especially monitoring the crop health at relatively cheaper expenditure over other remote sensing tools (Primicerio et al. 2012). Several researchers have reported the usage of geospatial technologies in different aspects of crop science which is presented in Table 1.3.

**Table 1.3** Major applications of geospatial technologies in crop and soil science

| Sl. no. | Application | Description | References |
|---|---|---|---|
| *Crop Science* | | | |
| 1. | Crop identification, crop type mapping | Multispectral satellite datasets are capable of identifying and mapping a crop by considering changes in reflectance as a function of plant phenology | Schmedtmann and Campagnolo (2015), Ghazaryan et al. (2018), Heupal et al. (2018), Lira Melo de Oliveira Santos et al. (2019), Zortea and Rodrigues (2019) and Sun et al. (2019) |
| 2. | Crop acreage estimation | The manual estimation of areas under crop is laborious and time consuming due to vast size of lands. Geospatial techniques can play a crucial role the estimation of the farmland on which a crop has been planted | Li et al. (2011), Pan et al. (2012), Craig and Atkinson (2013) and Rotairo et al. (2019) |
| 3. | Crop stress (nutrient, moisture, etc.) and crop condition health assessment | RS can play an important role in crop health monitoring and the extent to which the crop has withstood stress. Specific absorption bands of the plant pigment, crop moisture, and crop vigor are useful to assess crop condition | Katsoulas et al. (2016), Mee et al. (2017), Ennouri and Kallel (2019) and Virnodkar et al. (2020) |
| 4. | Crop yield and production forecasting and modeling | The expected crop yield and production over a given area or farmland can be estimated before harvesting of the crop using RS and GIS over a given period of time. It uses various crop information such as crop phenology, agronomic practices, crop weather, moisture level in the crops, soils map, etc. Nowadays crop yields are forecasted using RS input in combination with various statistical and machine learning approach using vegetation indices, phenology matrices, crop maps and yield proxies, etc. Crop growth simulation model enabled with in-season RS based crop biophysical parameters is an efficient tool in this aspect | Maki et al.(2017), Kasampalis et al. (2018), Huang et al. (2019), Ban et al. (2019) and Phung et al. (2020) |

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**Table 1.3** (continued)

| Sl. no. | Application | Description | References |
|---|---|---|---|
| 5. | Horticulture crop assessment and management | High-resolution satellite or aerial images are found to be highly suitable for mapping of horticultural and plantation crops. Due to its unique tree canopy and spacing, horticultural crop produce typical textural parameters of the image. This is utilized for rapid mapping and monitoring of the horticultural crops. The production estimates of horticultural crops are still under research and development | Trout et al. (2008), Usha and Singh (2013) and Marinelli et al. (2019) |
| 6. | Crop damage assessment | Crop damage can be due to unseasonal rainfall, hailstorm, pest and diseases, drought, and flood, etc. RS can be used to assess the crop area damage if there is large-scale destruction of crop canopy or leaf pigment. Current year anomalies with respect to normal year can also be a reasonable proxy for this purpose | Prabhakar et al. (2013), Zhou et al. (2016), Boschetti et al. (2015), Surek and Nador (2015) and Sawant et al. (2019) |
| 7. | Retrieval of crop biophysical parameters | The multispectral and hyperspectral indices are very useful for quantification of different biophysical and biochemical parameters like LAI, leaf chlorophyll contents and leaf moisture content, etc. Different canopy reflectance models are used for this purpose | Clevers and Kooistra (2011), Verrelst et al. (2015), Shelestov et al. (2017), Pasqualotto et al. (2019) and Darvishzadeh et al. (2019) |
| 8. | Crop insurance | High-resolution satellite data, drone, aerial images, proximal sensor can be used to assess crop growth, yield and extent of crop damage, delay in crop sowing, and moral hazards at farm level, and allow policymakers to provide insurance-related information for claim settlement. Geospatial technology can also provide objective solution of crop cutting experiment | De Leeuw et al. (2014), Borgogno-Mondino et al. (2019), Banerjee and Pandey (2019) and Valverde-Arias et al. (2020) |

(continued)

**Table 1.3** (continued)

| Sl. no. | Application | Description | References |
|---|---|---|---|
| 9. | Precision farming | PF can improve crop productivity with the aid of RS, GIS, and GPS, etc. It can help in analysis and management of spatial and temporal variability of farm inputs such as seeds, fertilizer, water, chemical, etc. within the field | Andreo (2013), Qiu et al. (2014), Mulla and Miao (2016), Hakkim et al. (2016), van Evert et al. (2017), Nabi et al. (2017), Castillejo-González (2018), Friedl (2018) and Neupane and Guo (2019) |
| 10. | Identification of pest and diseases infestation | RS approach particularly hyperspectral remote sensing can play a vital role in the monitoring pest and diseases infestation in the crop field and provide valuable data to adopt more accurate pest and diseases control mechanisms. Disease and pest forewarning system can also be developed using satellite and weather-based information | Ghobadifar et al. (2016), Mahlein (2016), Bhattarai et al. (2019) and Yones et al. (2019) |
| 11. | Identification of harvesting and planting dates | RS can monitor and observe weather pattern, crop climate, soil type, soil moisture, etc. which are useful to predict the planting and harvesting seasons of various crop based on area favorable for crop sowing. Time series satellite data analysis can also provide crop phenological metrics such as start of the season and end of the season | Chen et al. (2011) and Rolim et al. (2019) |
| 12. | Mapping of agricultural land use and crop sown area | The multispectral satellite data is useful to map land use and land cover for various functions such as crop growing and landscaping, etc. It can help in PA where specific land soils are used for specific purposes | Wu et al. (2014), Ambika et al. (2016), Useya et al. (2019) and Pareeth et al. (2019) |
| | Crop intensification | RS can be used to identify the in-season fallow area and also the single and double cropping systems. It can also be used to assess the suitability of taking up crops in the fallow land | Estel et al. (2016), Bégué et al. (2018), Löw et al. (2018) and Dimov et al. (2019) |

(continued)

**Table 1.3** (continued)

| Sl. no. | Application | Description | References |
|---|---|---|---|
| 13. | Crop biomass estimation | The rapid, reliable, and accurate economical estimation of crop above-ground biomass is possible through high-resolution spatial and temporal satellite data, hyperspectral data, drone, aerial images | Niu et al. (2019), Dayananda et al. (2019) and Han et al. (2019) |
| | Crop residues biomass | Geospatial technology along with crop statistics at administrative level can be used assess the spatial distribution of the surplus crop residue biomass and facilitate utilization of the same for biofuel/ biomass power plants | Wang et al. (2013) and Chakraborty et al. (2019) |
| *Soil Science* | | | |
| 1. | Soil survey and mapping | The most common and important application of RS in soil domain is soil mapping. Soil information as a form of map is useful for PA, crop growth simulation model, water balance studies, irrigation requirement, crop suitability assessment, etc. | Dwivedi (2001), Manchanda et al. (2002) and Mulder et al. (2011) |
| 2. | Soil moisture monitoring | RS techniques provide an alternative way to measure the spatial and temporal variability of soil moisture. Soil moisture can be retrieved either from optical/thermal/ microwave sensors or fusion of these sensors. Such data helps in estimation of the amount of moisture present in the soil and hence the type of crop that can be grown in the soil | Magagi et al. (2012), Wagner et al. (2013), Akbar and Moghaddam (2015), Zhang and Zhou (2016), Mohanty et al. (2017), Saha et al. (2018) and Mohamed et al. (2019) |
| 3. | Irrigation monitoring and management of irrigated agriculture | RS provides information about amount of soil moisture present in soil spatially and temporally. Such data can be used to determine whether a particular soil is moisture deficient or not which helps in irrigation scheduling | Taghvaeian et al. (2018), Tazekrit et al. (2018) and Ojo and Ilunga (2018) |

(continued)

**Table 1.3** (continued)

| Sl. no. | Application | Description | References |
|---|---|---|---|
| 4. | Wasteland mapping and land degradation assessment; identification of problematic soils | The advanced techniques such as microwave and hyperspectral and proximal ground-based sensor data with multivariate statistical algorithm have increased the efficiency of classification and mapping of degraded lands, problematic soils, etc. This allows experts to identify the areas under degradation and areas that are still intact. Such data are useful to develop action plan for land degradation neutrality for optimum productivity | Yiran et al. (2012), Mohamed et al. (2013), Vicente-Serrano et al. (2015) and Mao et al. (2018) |
| 5. | Soil erosion assessment and modeling | Satellite-derived environment parameters, DEM, LULC, vegetation cover, grid weather data are very useful to predict annual field-scale erosion rates through modeling approaches. Various process-based models, such as LISEM, EPIC, etc., are using space-based inputs to model soil erosion | Pandey et al. (2009), Karaburun (2010), Mitasova et al. (2013), Woldemariam et al. (2018) and Zabihi et al. (2019) |
| 6. | Digital/predictive soil mapping | Availability of DEM and high-resolution images and different environmental covariates allow to predict and generate spatial soil property map with the assistance of computer-based systems, modeling, or GIS. Such maps are very useful for precision farming and landscape and environmental modeling | Carré et al. (2007), Minasny and McBratney (2016), Sreenivas et al. (2016), Camera et al. (2017), Forkuor et al. (2017), Mitran et al. (2018b), Ma et al. (2019) and Wadoux et al. (2019) |
| 7. | Spatial variability of soil properties/nutrients | GIS is a very useful tool to generate spatial soil map from point-based field observation. This helps in assessing spatial variability of soil parameters, nutrient content which allow farmers to adopt site-specific nutrient management | Zhang et al. (2003), Vasu et al. (2017), Usowicz and Lipiec (2017), Teng et al. (2017) and Sharma and Sood (2020) |

(continued)

**Table 1.3** (continued)

| Sl. no. | Application | Description | References |
|---|---|---|---|
| 8. | Soil quality assessment | Geospatial techniques involving the use of RS, GPS, and GIS provide new approaches for studying various soil quality aspects in different spatial as well as temporal domains. Soil health assessment through spectral soil quality indexing is of major focus nowadays | Ben-Dor and Banin (1995), de Paul Obade and Lal (2013) and Paz-Kagan et al. (2014, 2015) |
| 9. | Soil fertility assessment and management | RS and GIS are important in the determination of soil management practices based on the soil fertility data collected from the fields | Blaes et al. (2016), AbdelRahman et al. (2016), Song et al.(2018), Molin and Tavares (2019) and Patel and Ghosh (2019) |
| 10. | Land suitability and capability assessment | Soil survey information coupled with RS data can be integrated in the GIS to evaluate crop suitability for different soils or vice versa. This helps in PA where specific soils are used for specific purposes | AbdelRahman et al. (2016), Yohannes and Soromessa (2018), Memarbashi et al. (2017), Parry et al. (2018), Purnamasari et al. (2019) and Murti (2019) |
| 11. | Soil nutrient deficiency | RS and GIS techniques can be used to determine the extent of soil and crop nutrient deficiency and facilitate the agricultural expert and farmers to come up with remedies that would increase the nutrients level in crops via soil hence improved the overall crop yield | Meng et al. (2015), Hengl et al. (2017) and Yousfi et al. (2019) |

## 1.8 Application of Geospatial Technologies in Soil Science

The conventional method of soil assessment is based on regular soil sampling design, sample collection, sample preparation, and subsequent chemical analysis in the laboratory. However, this approach is time-consuming, laborious, and costly to assess soil over a large area. Moreover, such a method can give you point-based information. Traditionally this information is represented as soil maps knowledge is represented as soil maps conforming to the discrete model of spatial variation (Heuvelink and Webster 2001). It shows polygons (represents homogeneous soils) with boundaries where changes in soil parameters are considered to be abrupt. However, the complete and accurate spatial information on soils is required for proper land use planning, soil management, and other activities linked to environmental protection. In nature soil properties are spatially variable therefore it should be estimated as a continuous variable rather than point values to have higher accuracy and wide applications. The recent advancement of RS, GIS, and GPS has enabled the researchers to assess land resources spatially and temporally. The availability of wide ranges of spatial and temporal satellite datasets make soil survey easier in the form of soil mapping. It can provide complete information about soil resources of an area which is utmost important for an effective agricultural research and advisory program. However, many soil properties can be better modeled with a continuous model of spatial variation using digital mapping approaches. The RS-based inputs along with secondary datasets such as slope, vegetation, climate, etc. allow for a more quantitative approach to soil survey producing continuous surfaces based on soil-forming factors which called “predictive” or digital mapping technique (Carré et al. 2007; Sreenivas et al. 2016; Mitran et al. 2018b). Besides, this approach gives spatial estimates of the uncertainty of the predictions. It uses a regression analysis between in situ point measurements of soil quality data and exhaustive satellite-derived indices to predict and upscale to larger areas spatially. The digital soil maps are also an ideal input for spatially distributed models. The satellite data along with digital soil map, land use, slope, and rainfall data derived from RS data can help in delineating major land degradation processes such as water and wind erosion, salt-affected soils, waterlogging, etc. along with its severity such as undegraded, moderately degraded, degraded, and severely degraded (Mohamed et al. 2013; Vicente-Serrano et al. 2015; Mao et al. 2018). A number of researchers have used RS and GIS techniques for soil taxonomic study or soil classification. GIS is also playing an important role in land resource inventories by assessing spatial variability of soil properties through interpolation techniques, that is kriging (Usowicz and Lipiec 2017; Teng et al. 2017; Sharma and Sood 2020). Nowadays introduction of hyperspectral remote sensing enables researchers to a more detailed analysis of soil fertility and quality (Paul Obade and Lal 2013; Paz-Kagan et al. 2014, 2015; Molin and Tavares 2019; Patel and Ghosh 2019). The quantitative prediction of soil properties, soil salinity, soil organic carbon content, $CaCO_3$ content, nutrient deficiency, etc. using hyperspectral data helps in formulating optimum soil management practices. The availability of microwave data helps in soil moisture estimation (Mohanty et al. 2017; Saha et al. 2018; Mohamed et al. 2019) and soil erosion studies (Woldemariam et al. 2018; Zabihi et al. 2019). RS and GIS have also played a crucial role in land suitability and capability assessment by identifying the problems associated with the soils (Memarbashi et al. 2017; Parry et al. 2018; Purnamasari et al. 2019; Murti 2019). Several researchers have reported the application of geospatial technologies in various aspects of soil science which is presented in Table 1.3.

## 1.9 Geospatial Technologies in Agriculture: Status and Challenges

The application of geospatial technologies and tools for sustainable resources management especially in agriculture has been advancing quite rapidly over the last decade in the Asia-Pacific region (Indonesia, Australia, Malaysia, Japan, etc.), South Asia (India), East Asia (China), Europe (Spain, Belgium, Netherlands), and in North America (USA, Mexico). A global survey was carried out by geospatial media and communication (2015) across the world (www.geospatialworld.net) and reported that 29% of the response to the survey use geospatial technologies for agricultural land use land cover mapping; 20% for crop inventory, acreage production, harvesting and storage; 19% for mapping of soil, water, and land; 13% for variable-rate technology; 7% for groundwater mapping and management; 12% for site suitability analysis. In the Asia-Pacific region, RS and GIS are mostly used for mapping of crops. Malaysia is mostly using RS and GIS for rice crop mapping and monitoring. Indonesia is using such technologies for producing digital maps and for land distribution of paddy field types. In Australia, these techniques are mostly used for mapping of oil palms and sugarcane. In India, satellite images are using for large-scale agricultural land use mapping, crop inventory, acreage estimation, crop production, storage, and harvesting studies. However, in Europe, these technologies are using for the automation of machinery and farm equipment, crop and water management, soil properties at a macro level, whereas agricultural land uses land cover mapping, wasteland mapping, etc. at a micro-level. Although the major RS data source in China is multispectral, they are using much higher spatial resolution data as well as hyperspectral data for agricultural monitoring. The major RS applications in agriculture in China are precision farming, crop yield, agricultural survey, and disaster forecasting. In North America, agricultural land use land cover mapping is the major use of geospatial techniques at a macro level, whereas crop disease assessment and site suitability analysis is at a micro level. The major micro-level applications of geospatial techniques are variable rate application and management of farm inputs (seeds, fertilizers, chemicals, etc.), groundwater zonation for irrigation suitability, drainage patterns, etc.

Geospatial technologies play an influential role in the agriculture sector by increasing yields, managing resources, prediction of outcomes, and improving farm practices. However, the application and adoption of geospatial technologies in agriculture are facing many problems and challenges, which vary from region to region across the globe. The challenges can be technology related, farm related, data related, and organization related. The major challenges at the organization level are lack of proper geospatial policies, skilled manpower, financial resources, etc. The lack of recent satellite images, topographic data, the spatial scale of data, unavailability of cloud-free data, data interoperability, and different data format are the major data-related challenges facing the agriculture sector to adopt geospatial techniques. Technology-related issues involved compatibility and high cost of hardware and software, lack of understanding in the correct application of the technology, inadaptability by the farmers at the grassroots, etc. Besides, a small landholding of the farmers, environmental issues, and farm ownership issues, identification and estimation of area and production of short-duration crops grown in fragmented landholdings, in particular during kharif/monsoon season, makes the geospatial technology application more challenging.

## 1.10 Conclusions and Future Prospective

The rapid development in the field of geospatial technologies especially the remote sensing and geographic information system play a key role to the sustainable management of natural resources through extraction of the precise and desired information to save the costly and infinitive natural resources for the future generation. Remote sensing data at the optical, microwave, thermal, and hyperspectral domain has proved to be a powerful tool to assess the crop and soil properties in varying spatial and temporal scales with cost-effectiveness. Remote sensing satellite images can be used efficiently for crop growth monitoring, crop condition assessment, crop acreage and yield estimation, precision farming, crop biomass estimation, identification of pest and diseases infestation, soil survey and mapping, land degradation assessment, soil moisture estimation, soil quality assessment, etc. Geographic Information System is considered one of the important tools for decision-making in a problem-solving environment dealing with geo-information. Such technologies and tools can be used effectively for developing optimum management strategies or suitable action plans to maintain the agricultural sustainability of any province. It is a novel approach to save the energy consumption directly and indirectly, reduce input and footprints of the ecosystems, and enhance the eco-intensification of the natural resources for the food, nutritional, environmental, and economic security to the growing population.

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