ISBN: 978-81-968830-3-4

8. Recent Advances in Remote Sensing

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Abstract:

Remote sensing has emerged as a powerful tool for earth observation. In recent years, remarkable advancements in remote sensing technologies have been noticed. These technologies have enabled more accurate and detailed data acquisition systems.

Sensors' performance in terms of spatial, spectral, and temporal sensing abilities has expanded far beyond the traditional boundaries of remote sensing, resulting in significantly better observation capabilities. Similarly, Remote sensing field is experiencing unprecedented developments recently in sensor platforms like satellites, unmanned aerial vehicles (UAVs), and ground-based platforms, which give better observation of earth surface. Advancements in data acquisition techniques such as LiDAR, SAR and hyperspectral imageries revolutionize the remote sensing field. The diversity of objectives and the unique characteristics of the data give rise to the use of a wide range of data processing algorithms like machine learning and deep learning. An overview of these types of advancements is reflected in this chapter. Additionally, current challenges and future direction is also highlighted to minimize and overcome challenges with new advanced technologies.

Keywords:

Remote Sensing, Unmanned Aerial Vehicles, Nanosatellites, Machine Learning, Deep Learning.

8.1 Introduction:

Remote sensing is the science and art of obtaining information about an object, area, or phenomenon from a distance without physical contact. It requires sensors on satellites, aircraft, drones, or ground-based platforms to capture data, which is used to analyse and interpret valuable information. Acquiring data remotely provides a unique outlook of Earth's surface and atmosphere, allowing for large-scale observations. Due to unprecedented technological developments, the remote sensing field has been vastly expanded in terms of applications recently, and in parallel, the performance has significantly improved too [1]. Remote sensing has emerged as a powerful tool with significant applications in various fields, such as environmental monitoring [2, 3, 16-18], agriculture and forestry [4, 5, 19-22], urban planning [6, 7, 23, 24], and disaster management [8, 9, 25, 26]. This remote sensing capability has helped understand and address complex challenges to the scientist, researchers, and policymakers.

In recent years, remarkable advancements in remote sensing technologies have been noticed. These technologies have enabled more accurate and detailed data acquisition systems. With time remote sensing sensor technologies have been improved. Sensors' scope and performance potential in terms of spatial, spectral, and temporal sensing abilities have expanded far beyond the traditional boundaries of remote sensing, resulting in significantly better observation capabilities [10]. Due to ever-advancing technologies, the remote sensing field is experiencing unprecedented developments recently, fuelled by advancements and continuously increasing information infrastructure of sensor platforms like satellites, unmanned aerial vehicles, and ground-based platforms [10]. Hyperspectral remote sensing has enhanced object discrimination and classification based on spectral signatures [11, 12]. Synthetic Aperture Radar (SAR) has been revolutionized for all-weather imaging capabilities in remote sensing [4, 13]. LiDAR technology made high-resolution 3D mapping and terrain modelling very easy [7, 14]. Advancements in data processing algorithms like machine learning and deep learning have also played a crucial role in extracting valuable information from remote sensing data [2, 15]. These advances, along with others, have expanded the applications and capabilities of remote sensing. These newly emerged technologies can provide valuable information for decision-making activity.

This chapter provides an overview of remote sensing, its importance in several fields, and recent technological advancements. It aims to highlight the advancement of remote sensing and its significance to researchers. Researchers and decision-makers can help solve problems and reach beneficial conclusions in various fields by recognizing the potential of newly emerged remote sensing technologies.

8.2 Sensor Technology:

8.2.1 Advancements in Sensor Technology:

Now a day’s sensor technology plays a crucial role in remote sensing. Advancement in sensor technologies with time has a significant contribution to the progress and capabilities of remote sensing [27]. These advancements include spatial and spectral resolution improvements, radiometric accuracy, and temporal coverage.

Spatial resolution is a measure of the smallest object that can be resolved by the sensor, or the ground area imaged for the instantaneous field of view (IFOV) of the sensor, or the linear dimension on the ground represented by each pixel [34]. Over the years, sensor technology has advanced to provide higher spatial resolution imagery. Higher spatial resolution allows for identifying and characterizing smaller and more complex objects on the Earth's surface. Spatial resolution may vary from 1000 meter to few meters also. Sensors having low spatial resolution such as MODIS spatial resolution of 250m, 500m and 1000m are useful for large or broad scale study. When come to detail study of an area sensor having high to very high spatial resolution is required. In such cases Landsat (Panchromatic band of 15m and multi-spectral band of 30m spatial resolution) and Sentinel (spatial resolution of 10, 20 and 60m) satellite images are widely used in recent days. Some commercial satellites can now give up to 0.5 meter of spatial resolution. Gaofen-2 (0.8m Pan band, 3.2m multi-spectral band), WorldView-3 (30cm pan band and 1.24m multi-spectral band) can be used for detail study of earth surface.

This type of advancement in spatial resolution can help in Land use and Land cover mapping [28], Discriminating tree species [29], and yield estimation of agricultural crops [30] in real-time scenario where requirements of high-resolution satellite data is important.

The spectral resolution describes the number and width of spectral bands in a sensor system. Modern sensors are designed to capture data in multiple spectral bands across the electromagnetic spectrum [34]. This broader spectral coverage allows for detecting and discriminating various materials and phenomena based on their unique spectral signatures. Many sensor systems have a panchromatic band, which is one single wide band in the visible spectrum, and multispectral bands in the visible-near-IR or thermal-IR spectrum. Advancements in sensor technology have led to the development of hyperspectral sensors, which capture data in numerous narrow and contiguous spectral bands, for example, Hyperion on EO-1 satellite has 242 bands at 30-m spatial resolution. This can enable more precise identification and characterization of crop stress [31], weed infestation [32], crop biophysical and biochemical properties' mapping, soil characteristics, and crop classification [33] in the field of Agriculture.

Temporal coverage refers to the frequency and regularity of image acquisitions over a specific area. The frequency characteristics are determined by the design of the satellite sensor and its orbit pattern. In the past, remote sensing data was limited to infrequent captures due to limitations in sensor availability and satellite revisit times. However, advancements in sensor technology have led to increased temporal coverage. Satellites with shorter revisit times, constellations of satellites, and the integration of multiple sensor platforms have enabled more frequent and consistent monitoring of the Earth's surface [34]. Advancement in temporal coverage is valuable for tracking dynamic processes, such as crop growth, frequent forest fire detection, land cover changes, and natural disasters.

Radiometric accuracy refers to the ability of a sensor to accurately measure and record the energy reflected or emitted by objects. Improvements in radiometric accuracy have led to more reliable and consistent measurements, reducing uncertainties in the data [34]. This enhancement is crucial for accurate quantification applications, such as monitoring changes in vegetation health, assessing atmospheric pollutants, and studying surface temperature variations etc.

8.2.2 New Sensor Platforms:

A platform serves as a stage from which valuable data about a target under investigation is acquired through sensors or cameras. The advancement of modern sensor platforms, such as satellites, unmanned aerial vehicles (UAVs), and ground-based platforms, enhances the field of remote sensing. These platforms have extended the capabilities and applications of remote sensing.

Satellites are vital in remote sensing, providing global coverage and long-term monitoring capabilities. In 1972 the first civilian earth-observing satellite, Landsat 1, was launched to collect imagery of the Earth's surface [35]. With time the number of imagery-collecting satellites has increased with more Landsat satellites (Landsat 8 and 9), MODIS, and Sentinel [36].

Some commercial satellites such as World view-3, Rapid Eye, and GeoEye-1 are also launched [34]. These satellites collect data with higher spatial, spectral resolution and shorter return frequency, making them useful in a variety of field operations.

Wide varieties of ground-based platforms are used in remote sensing. Some of the common ones are handheld devices, tripods, towers, and cranes. When studying individual plants or small patches of grass, ground-based platforms like handheld devices or those mounted on tripods are used widely. On the other hand, permanent ground platforms like towers and cranes serve specific purposes, such as monitoring atmospheric phenomena and long-term observation of terrestrial features. The proximity of data collection significantly reduces atmospheric interference, resulting in enhanced accuracy and higher spatial resolution. Moreover, ground-based sensors are particularly well-suited for applications involving smaller fields [37].

Unmanned aerial vehicles (UAVs) are commonly known as drones. Nowadays, UAVs are being used in almost every field that needs observed information from the top or oblique views. Equipped with imaging sensors, UAVs can collect high-resolution aerial imagery with flexibility and proficiency. The characteristics of UAVs with low flying altitude, low cost, and high flexibility provide new opportunities for remote sensing applications in various areas with high spatial resolution, high-frequency, and multi-source data [37, 41]. UAVs are particularly useful for applications that require fine-scale mapping, such as precision agriculture [38]. UAVs has a various scenario of applications of in smart agriculture like including irrigation, fertilization, use of pesticides, weed management, plant growth monitoring, crop disease management, and field-level phenotyping [39-41]. Besides agriculture UAVs have influenced researchers in other sectors also. Li et al. [4] observed that LiDAR based UAV techniques were an efficient and reliable method for surveying terrain making them highly important for creating high accurate flood simulation model. Similarly, Casagli et al. [42] found space borne, UAV and ground-based remote sensing were useful technique for mapping, monitoring and early warning of landslide. For Marine-Coastal Environment Monitoring UAV based wireless network system can be used [43]. So, UAV based remote sensing are an appealing option for local and time-sensitive remote sensing applications due to their relatively low cost and rapid deployment time.

Nanosatellites have gained popularity due to their low cost and short development cycle. This type of feature made nanosatellite constellations an affordable option for observing the Earth from a remote sensing point of view [44]. The first nanosatellites were launched between 1958-1968. Minimization technologies were evolving in nanosatellites with time. Commonly known as nanosatellites, CubeSats started successfully flying in 2003 [45]. After that, this nanosatellite made a revolutionary change in remote sensing. Advancements in sensor platforms like nanosatellite technology have led to higher spatial and spectral resolution imagery availability, enabling more detailed and precise analysis. The Planetscope (PS) constellation of more than 130 nanosatellites from Planet Labs revolutionizes the high-resolution vegetation assessment [46]. Sustainable crop practices under changing climate condition, understanding the climatic parameters and water requirements with vegetation can be evaluated for detailed study using nanosatellites like Planetscope [46, 47]. This unprecedented combination of high spatial and temporal resolution achieved by nanosatellite constellations could herald a shift towards replacing large and expensive satellites with smaller, more cost-effective nanosatellites [44].

8.3 Data Acquisition and Processing:

8.3.1 Data Acquisition Techniques:

Recent developments in data acquisition techniques have brought about significant advancements in remote sensing. Advancement in LiDAR technology was noticed rapidly after the invention of the laser in 1960. Various LiDAR technologies have developed during the last 60 years to support advancement in digital models of terrain ecology, hydrology, atmospheric science, and oceanography [48]. LiDAR is a remote sensing technology that uses laser pulses to measure distances. It operates by emitting laser beams and measuring the time it takes for the light to reflect from the Earth's surface. LiDAR techniques capture a dense point cloud of millions of individual data points, allowing for the generation of high-resolution 3D models of the terrain and objects [7]. It provides detailed information on elevation, vegetation structure, building heights, and terrain characteristics [49]. LiDAR sensors mounted on cheaper ground-based platform or drones can be very effective for forestry, especially for canopy height and width [50, 51]. Muhadi et al. [52] found that LiDAR-derived data were helpful in flood risk management, especially in the future assessment of flood-related problems. In the field of agriculture, LiDAR technology has so many applications. Debnath et al. [53] highlighted the applications of LiDAR technology, such as leaf area index and canopy volume measurement, crop biomass estimation, canopy phenological stages and phenotype identification, weed detection, crop growth estimation, soil property detection, yield prediction and crop damage detection in their study.

Synthetic aperture radar (SAR) is a remote sensing technique that uses microwave signals to acquire images. Since the launch of the first SAR satellite by the United States, SAR has received extensive attention in the remote sensing community [13]. Unlike optical sensors that rely on sunlight, SAR systems emit microwave pulses and measure the backscattered signals. SAR operates in all weather conditions and at any time of day, as microwaves are unaffected by clouds, fog, or darkness. This capability makes SAR data useful for different applications on the Earth's surface. Starting with the launch of European Space Agencies' Sentinel-1a in 2014, SAR data have been widely used in different fields of study. Some other Satellites which give SAR data are RADARSAT-2, ENVISAT, ERS-1 and 2 etc. [13, 55]. Therefore, it is valuable and meaningful to study SAR-based remote sensing applications. SAR data allows further application development in agriculture, particularly crop type mapping, crop condition assessment, vegetation density, soil tillage and crop residue mapping, and soil moisture estimation [4, 55].

Hyperspectral imaging captures data in numerous narrows, contiguous spectral bands across the electromagnetic spectrum. Traditional multispectral imaging typically captures data in a few broad bands. Hyperspectral remote sensors achieve imagery data through hundreds of adjoining spectral bands that provide detailed spectral information [11]. This advancement allows the precise identification and characterization of materials based on their unique spectral signatures [55]. Hyperspectral remote sensing can enable more precise identification and characterization of crop stress [31], weed infestation [32], crop biophysical and biochemical properties' mapping, soil characteristics, and crop classification [33] in the field of Agriculture. Mineral exploration and environment monitoring can be possible using hyperspectral remote sensing [56, 57].

Shang and Chisholm [58] successfully classify native forest spices using hyperspectral remote sensing and machine learning algorithms. Like this, in Surveillance and Environment field where the discrimination of subtle differences in spectral reflectance is crucial hyperspectral remote sensing plays a vital role.

8.3.2 Data Processing Algorithms:

Advancements in data processing algorithms have played a crucial role in extracting valuable information from remote sensing data. Different types of remote sensing datasets make it possible to overcome common problems associated with geological features. The rapid increase in the volume of remote sensing data obtained from different platforms has encouraged scientists to develop advanced, innovative, and robust data processing algorithms [59]. Similarly, the diversity of objectives and the special characteristics of the data give rise to the use of a wide range of data processing algorithms [60].

Machine learning (ML) algorithms are designed to enable computers to learn and make predictions or decisions based on data patterns and examples. It is a collection of a variety of algorithms (e.g., neural networks, support vector machines, decision trees, self-organizing map, random forests, case-based reasoning, genetic programming, etc.) that can provide multivariate, nonlinear, nonparametric regression or classification [60]. Hence, ML has an effective approach for solving problems in geosciences and remote sensing [61]. It can help in processing a wide range of remote sensing datasets and determine the relationship between components. M. Anul Haq [46], Maskooni et al. [62], and Shang et al. [58] highlight the ML algorithms to solve complex problems in the field of remote sensing. Artificial neural networks (ANN) and support vector machines (SVM) are the most commonly used ML algorithms for dealing with remote sensing problems [61]. Lary J.D. [63] explained the detail application of ANN and SVM in remote sensing. These algorithms enable automated and efficient analysis of large remote sensing datasets, improving the accuracy and speed of data processing.

Deep learning (DL) is a subset of machine learning that utilizes artificial neural networks with multiple layers to extract complex patterns and hierarchical representations from data. These algorithms can automatically learn and extract features from raw remote-sensing imagery. DL can reduce the need for manual feature engineering.

Ma et al. [15] gave a detailed review of how DL has been applied for remote sensing image analysis tasks including image fusion, image registration, scene classification, object detection, land use and land cover classification, segmentation, and object-based image analysis. Since the rise of deep learning in the past few years, convolutional neural networks (CNNs) have rapidly found their place within the remote sensing community [64]. CNNs are one of the most extensively used deep learning models that have shown remarkable performance in image analysis tasks.

As a result, they have transitioned away from other machine learning techniques, achieving unprecedented improvements in many specific RS applications [64]. Deep learning techniques have significantly improved the accuracy of land cover mapping [65, 66], change detection [67, 68], and other image classification tasks [69, 70] in remote sensing.

Various Earth observation satellites offer various types of remotely sensed data products. These products include panchromatic, multispectral, hyperspectral, and SAR imagery, covering different electromagnetic spectrum parts. This remote sensing data are further processed and used for different purposes. From a single data product, getting more valuable information is insufficient in some remote sensing fields. It is better to get complementary information from more than one sensor to understand a surface. So, image fusion technique becomes the best option to integrate the best information collected from different sensors at different spatial, spectral, temporal, and radiometric resolutions [71]. Image fusion techniques involve combining multiple remote sensing images or data sources to produce a single, enhanced output with more comprehensive information. Fusion can be done at various levels, including pixel-based, feature-based, or decision-based fusion [72, 73]. Image fusion techniques aim to overcome the limitations of individual images, such as limited spatial resolution or spectral coverage or weather condition. For example, optical with SAR, to produce fused images that retain the best characteristics of each source which improves the interpretability and analysis of remote sensing data, enabling a more holistic understanding of the Earth's surface or features [74].

8.4 Integration with Other Technologies:

Integrating remote sensing with other technologies, such as geographic information systems (GIS), Internet of Things (IoT) has significantly enhanced the capabilities and applications of remote sensing data. GIS provide a framework for managing, analyzing, and visualizing geospatial data. When integrated with remote sensing, GIS allows for integrating remote sensing imagery and derived products with other spatial data layers, such as maps, satellite imagery, and socioeconomic data. This integration enables the spatial analysis of remote sensing data and facilitates the extraction of meaningful information [75].

The Internet of Things (IoT) involves the interconnection of various devices and sensors through the Internet [76]. This can enable the collection and sharing of real-time data. Integrating IoT with remote sensing expands the data collection capabilities and enhances remote sensing systems' spatial and temporal coverage. For instance, environmental monitoring stations equipped with IoT sensors can provide complementary data to remote sensing platforms [81, 82]. This integration allows for better calibration, validation, and integration of remote sensing data, which leads to more accurate and reliable analysis [82]. IoT-enabled remote sensing applications can provide real-time monitoring and alerts for precision agriculture, weather forecasting, and disaster management.

8.5 Challenges and Future Directions:

8.5.1 Current Challenges:

The field of remote sensing faces several challenges that need to be addressed to maximize its potential and overcome limitations. Despite the remarkable progress made in remote sensing technologies, data availability remains a persistent concern in the scientific community. While satellites offer valuable insights, their revisit times can pose limitations, especially when researchers require high-resolution data at frequent intervals. The presence of cloud cover further complicates matters by corrupting satellite imagery.

UAVs provide a promising alternative for data collection, but they have their challenges. Weather conditions, such as rain or snow, can affect UAV operations [38]. Additionally, the limited flight times of UAVs may necessitate refuelling or carrying extra batteries to complete the required missions [37]. Another option involves handheld sensors or mounting sensors on vehicles. However, this approach is often laborious and time-consuming for large fields. Researchers strive to find efficient and effective data-gathering solutions [37]. The current data availability and collection limitations remain critical difficulties that require innovative approaches and technological advancements. Accurate and reliable remote sensing data is essential for meaningful analysis and decision-making [77]. However, challenges such as sensor limitations, atmospheric effects, and geometric distortions can impact data quality. To address this, accurate calibration and validation procedures are necessary. Field measurements and establishing ground truth reference data can help assess and ensure data accuracy. Standardized protocols and quality assurance frameworks maintain data integrity and enhance comparability between datasets, sensors, and platforms. One of the challenges in remote sensing is handling the vast amounts of data generated by different platforms. Effective data management strategies are crucial to ensure efficient storage, accessibility, and data sharing. Developing scalable storage systems, implementing data compression techniques, and establishing standardized metadata and cataloguing methods can streamline the process. Cloud-based solutions and distributed computing frameworks offer easier access and collaboration among researchers and users.

8.5.2 Future Direction:

The field of remote sensing is continuously evolving. Several potential future directions and trends are shaping its development. Nanosatellites have gained significant attention recently due to their low-cost, rapid development, and deployment capabilities. Nanosatellites offer potential opportunities for remote sensing applications by providing enhanced spatial and temporal coverage [44]. Using nanosatellites in remote sensing opens up possibilities for cost-effective and agile data collection, especially in areas with limited traditional satellite missions [44, 45]. Hyperspectral imaging captures data across a wide range of the electromagnetic spectrum, allowing for detailed spectral analysis and materials and vegetation types identification. Future advancements in hyperspectral imaging technology aim to improve spectral resolution, spatial resolution, and data processing capabilities. These advancements in hyperspectral techniques enhance remote sensing capabilities and enable more precise and comprehensive use in remote sensing. Integrating remote sensing with emerging technologies like blockchain and augmented reality opens up new data management, analysis, and visualization possibilities. Blockchain technology can enhance remote sensing applications' data security, authenticity, and traceability. It enables data owners to share the data without an intermediary, keeps track of the data updates and provides a quality score, and overcomes the issue of untrusted data owners [78]. Augmented reality (AR) can enhance the visualization and interpretation of remote sensing data by overlaying virtual information on real-world scenes. AR-based remote sensing applications can provide user's real-time data visualization, interactive analysis tools, and immersive experiences [79].

Researchers, industry professionals, and policymakers must collaborate to minimize and overcome changes with new technologies, sensor platforms, data storage, and security prospects.

Investment in data infrastructure, the development of standardized protocols, and quality assurance frameworks are essential for the responsible and sustainable use of remote sensing data.

8.6 Summary and Conclusion:

In conclusion, this book chapter has provided a comprehensive overview of recent advances in remote sensing and their significance in various fields. The discussion encompasses the advancements in remote sensing that have led to improvements in spatial and spectral resolution, radiometric accuracy, temporal coverage, and data acquisition platforms such as ground-based platforms, UAVs, and satellites. These advancements have expanded remote sensing capabilities, enabling more detailed and comprehensive observations of the Earth's surface. Developing new sensor platforms like nanosatellites has offered cost-effective and agile data collection capabilities. Moreover, the advancements in data acquisition techniques, such as hyperspectral imaging, LiDAR, and SAR, have enhanced the extraction of valuable information from remote sensing data.

The chapter highlights the significance of advancements in data processing algorithms, such as machine learning, deep learning, and image fusion techniques. These algorithms facilitate extracting valuable insights and patterns from remote sensing data, which leads to more accurate and efficient analysis. Furthermore, integrating remote sensing with other technologies, including GIS, big data analytics, and IoT, enhances the utility of remote sensing data for advanced spatial analysis, data management, and decision-making processes.

The chapter also acknowledged the current challenges in remote sensing, such as data availability, quality assurance, storage and management. Addressing these challenges is crucial for ensuring responsible and sustainable use of remote sensing data. Lastly, potential future directions and trends in remote sensing were discussed.

These future directions present exciting possibilities for advancing remote sensing capabilities and expanding applications. Recent advancements in remote sensing have significantly enhanced our ability to observe, analyze, and understand the Earth's surface. The integration of these advancements in sensor technology, data acquisition, processing algorithms, and integration with other technologies has opened up new opportunities for addressing critical challenges in various fields. As we continue to push the boundaries of remote sensing, further breakthroughs can be expected, revolutionizing our understanding of the Earth and supporting sustainable development efforts.

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