

REVIEW

Advances in Hyperspectral Remote Sensing for Sustainable Natural Resource Management

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ABSTRACT

Hyperspectral remote sensing has emerged as a transformative technology for sustainable natural resource management by providing unprecedented insight into the biochemical, biophysical, and compositional properties of Earth's surface. The high spectral resolution of hyperspectral sensors allows a very specific discrimination of materials, monitoring of environmental stress at a very early stage, and provides quantitative retrieval of ecological and geochemical parameters in a wide range of landscapes. The booming technology in sensor design, machine learning, spectral unmixing, and multi-sensor data fusion has further improved the analysis potential and application of imaging spectroscopy to a large extent. This paper involves a discussion of the oversight of such technological advances and the manner in which they are utilized in the principal fields that include forestry, agriculture, water, mineral exploration, and coastal ecosystems. Case studies allow us to identify the potential practical consequences of both spaceborne and unmanned aerial vehicles (UAV)-based hyperspectral systems and AI-based workflows that can be used to aid in more efficient and accurate environmental review. Even though the issues associated with data volume, atmospheric impacts, lack of uniformity in the calibration process, and socioeconomic limits continue to exist, the new technology in sensor miniaturization, cloud computing, and artificial intelligence indicates a fast-changing environment. All these

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developments make hyperspectral remote sensing a key instrument in solving global sustainability problems and evidence-based management of natural resources in an evolving world.

Keywords: Hyperspectral Remote Sensing; Sustainable Natural Resource Management; Imaging Spectroscopy; Machine Learning; Environmental Monitoring

1. Introduction

The increasing forces of the world population, economic progress, and climate change have put more pressure on natural resources than ever. Forests, agricultural land, water sources, and mineral deposits are all under increasing pressure of degradation due to unsustainable exploitation, conversion of land use, and increased environmental stressors. All these issues highlight the fact that there is a pressing need to have strong, spatially holistic, and temporally consistent monitoring instruments in order to inform sustainable management and policy making. Remote sensing has a long history of being a pillar in environmental assessment because it allows the observation of the surface processes on Earth on a large scale. Nevertheless, the standard multispectral systems prevailing in operational surveillance cannot be used to monitor subtle biochemical and biophysical variations necessary in early warning measurements and to characterize resources at a finer level ^[1,2].

Hyperspectral remote sensing (HRS) or imaging spectroscopy is a groundbreaking development in Earth observation. Hyperspectral sensors imprint fine spectral bands, producing hundreds of adjacent, narrow spectral bands that disclose the chemical makeup, form characteristics, and physiological state of natural products. The high spectral resolution is able to discriminate vegetation species, measure soil and water components, and identify mineralogical differences that commonly remain hidden with multispectral systems. Recent developments in airborne and spaceborne hyperspectral missions, like *PRISMA* (IperSpettrale della Missione Applicativa), the Environmental Mapping and Analysis Program (EnMAP), the DLR Earth Sensing Imaging Spectrometer (DESI), and future missions, including the National Aeronautics and Space Administration (NASA) Surface Biology and Geology (SBG) program, have seen a dramatic increase in the availability, spatial scale, and scientific capability

of HRS data. At the same time, the high-resolution and local-scale environmental assessment possibilities afforded by the development of lightweight hyperspectral cameras on unmanned aerial vehicles (UAVs) represent new possibilities in this regard ^[3-5].

Even though it has a massive potential, the integration of hyperspectral technologies in the day-to-day management of natural resources has been limited due to a number of challenges. Hyperspectral data are high-dimensional, computationally expensive, and sensitive to atmospheric and light conditions. It demands complex pre-processing pipelines, machine learning and deep learning models, and spectral libraries of the domain to be analyzed. Furthermore, the conversion of hyperspectral information into management action has to be undertaken by interdisciplinary teamwork and operation structures that have the capability of closing the gap between research innovation and practical application.

In recent years, the fast development of artificial intelligence, sensor miniaturization, data fusion, and cloud processing has started to solve those problems and pave some new ways on the way to operational implementation in sustainability science. These methodological and technological innovations have now allowed more precise mapping of the species level in forests, greater detection of crop-level stress in crop systems, accurate quantification of water quality parameters, and increased geological and mineralogical features. With the increasing environmental demands that are felt all over the world, hyperspectral remote sensing will be an indispensable instrument of evidence-based governance of natural resources ^[6,7].

This article presents a review of the recent developments in hyperspectral remote sensing with a special emphasis on its use in the management of the sustainability of natural resources. We look at the basic principles of hyperspectral imaging, talk about the latest data processing algorithms, and estimate the use of this technique in forestry, agriculture, water resources, mineral exploration, and

coastal areas. We also emphasize the current issues and future research interests that are required to fully harness the capability of hyperspectral technologies in aiding sustainability goals on an international basis ^[8–12].

Figure 1 displays the workflow of hyperspectral remote sensing, including data collection using satellite, airborne, and UAV sensors, preprocessing, advanced image processing, and information products to support decision-making. The diagram focuses on the chronological in-

tegration of data preparation, computational analysis, and practical implementation, and on how new developments in machine learning and deep learning can improve them. The reader must realize that this workflow does not necessarily follow a linear progression: feedback mechanisms (e.g., validation with field measurements or UAV imagery to enhance the accuracy of analysis and natural resource management) are essential to improve the accuracy of the analysis.

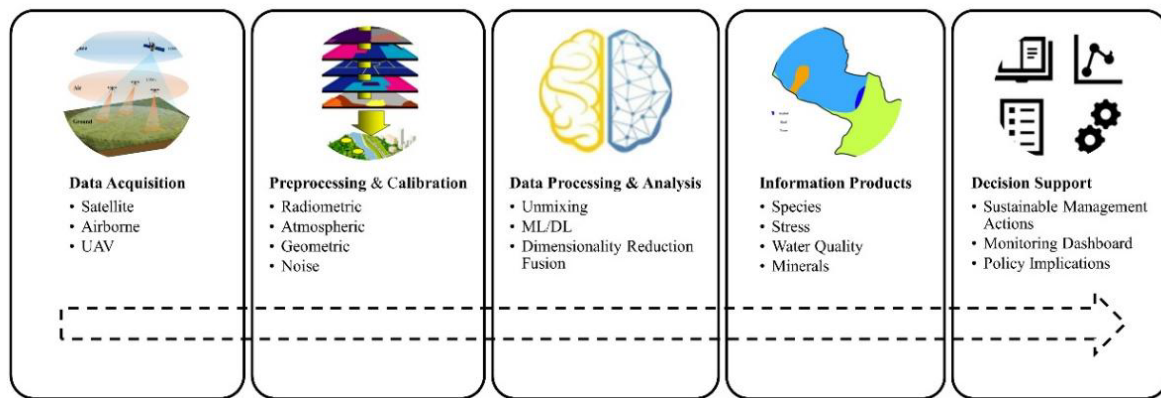


Figure 1. Conceptual Workflow of Hyperspectral Remote Sensing for Natural Resource Management ^[11,12].

Figure 1 illustrates the end-to-end workflow of hyperspectral remote sensing, from data acquisition across satellite, airborne, and UAV platforms to preprocessing, advanced analysis, and the generation of information products for decision support. The figure emphasizes the sequential integration of data preparation, computational analysis, and practical application, highlighting how advances in machine learning and deep learning can enhance each stage. Readers should understand that this workflow is not strictly linear: feedback loops, such as validation using field measurements or UAV imagery, are crucial for refining analysis and improving accuracy in natural resource management.

2. Fundamentals of Hyperspectral Remote Sensing

Imaging spectroscopy or hyperspectral remote sensing (HSR) is characterized by the capacity to record detailed continuous spectral data in hundreds of narrow, adjacent wavelength bands. This has allowed the accurate definition of the surface materials in terms of their indi-

vidual reflectance and has established HSR as a key technology in the role of advanced earth observation. It is important to realize the physical basis, sensing platforms, and necessary pre-processing before interpreting hyperspectral data and using it in an effective way in natural resource management ^[13,14].

2.1. Principles of Hyperspectral Imaging

Hyperspectral remote sensing (HSR) or imaging spectroscopy is based on the idea of measuring fine spectral detail over a huge number of adjacent, narrow bands of wavelengths. In contrast to multispectral sensors, which record reflectance data in one or two broad spectral bands, hyperspectral sensors can cover a spectrum range of the visible (given that it is shortwave) to shortwave infrared with spectral steps as brief as a few nanometers. This spectral sampling can be used to obtain continuous reflectance curves for each pixel in an image, tracing the fine and diagnostically significant features of absorption which are associated with certain biochemical or mineralogical constituents. An example of this is that a change in the pigment levels, the water content of the leaves, or the struc-

ture of the canopy can give rise to typical inflections in vegetation spectra, whereas clay minerals, carbonates, and iron oxides have been found to have recognizable absorption signatures in the infrared regime. This has led to the distinctly powerful ability of hyperspectral imaging to determine, discern, and measure the large variety of natural materials at the Earth's surface. HRS is especially suited to environmental monitoring and resource evaluation due to the possibility of identifying spectral variations related to the physiology of stress, compositional variations, or gradients in the environment ^[15,16].

2.2. Spectral Signatures and Material Discrimination

The diagnostic capability of hyperspectral data is due to the fact that each material uniquely responds to electromagnetic radiation, creating a spectral signature of its chemical makeup, physical structure, and moisture or pigment content. The spectral reflectance in vegetation is determined by the pigment absorption within the visible spectrum, the steep red end spectrophotometry linked to the activity of the chlorophyll, and the various water absorption characteristics in the near- and shortwave-infrared spectra. These diagnostic spectral values are represented as representative hyperspectral reflectance signatures of vegetation, soils/minerals, and water bodies (Figure 2). These characteristics are subject to predictable changes in environmental stress, such that the physiological changes are detected early before they can be observed by the human eye. The spectral characteristics of soils and rocks are related to the vibrational characteristics of minerals, which can then be used to differentiate the types of clays, to identify alteration minerals that have an interest in geological exploration, and to map the soil organic matter or salinity. In inland and coastal waters, spectral variation is affected by dissolved organic matter, phytoplankton pigments, suspended sediments, and bottom reflectance in the shallow systems. Since the spectral data from hyperspectral sensors are in finely resolved spectral samples, they can be used not only to classify surface materials but also to recover quantitative biogeochemical parameters. Such a capacity to unmix and analyze complicated spectral responses forms the basis of most of the modern methods of sustainable management of natural resources ^[17-19].

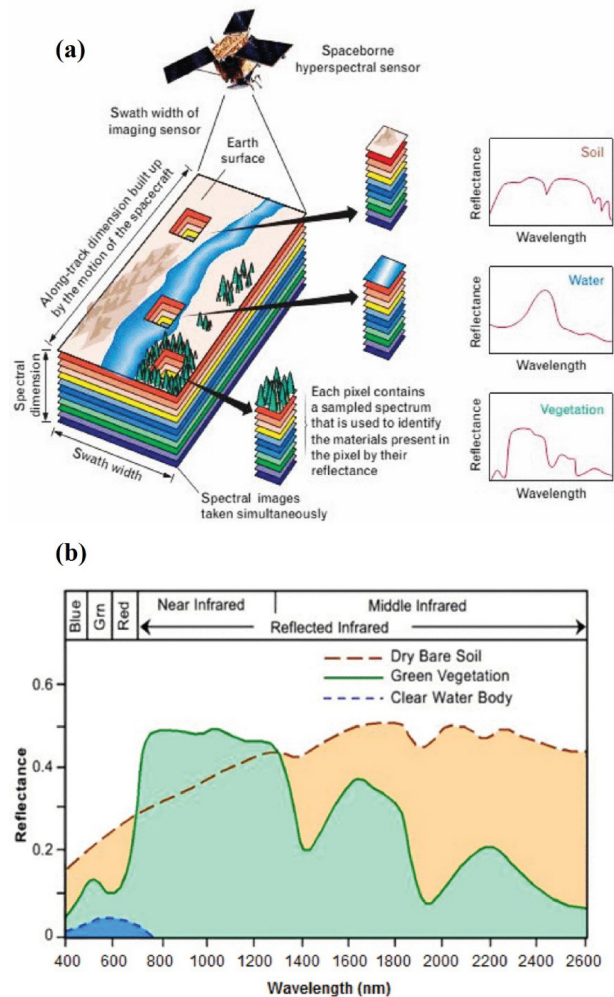


Figure 2. (a) A general hyperspectral imaging mapping scheme; (b) spectral response curves for soil, vegetation, and water ^[19].

2.3. Hyperspectral Data Acquisition Platforms

Hyperspectral data are taken on a variety of platforms, each with its own benefits towards monitoring the environment. Airborne hyperspectral systems have traditionally demonstrated the highest spectral and radiometric quality, along with the ability to target specific locations under controlled flight conditions. Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) and Hyperspectral Mapper (HyMap) are examples of instruments that have been the foundation of algorithm development and environmental analysis over the last decades, and which have allowed scientists to map ecosystems, evaluate geological structures, or measure the quality of water at extremely fine scales. Conversely, over the past few years, spaceborne hyperspectral missions have increased by a wide

margin, offering regular, worldwide imaging spectroscopy of wide scope. PRISMA, EnMAP, and DESIS have become sensors capable of providing a uniform calibration and standardized acquisitions over large areas, to study vegetation health, soil properties, mineralogy, and coastal environments. These missions are a major milestone in operational hyperspectral Earth observation, and new missions like the NASA Surface Biology and Geology (SBG) mission are anticipated to increase the frequency of observations and radiometric stability. On smaller spatial scales, the development of lightweight hyperspectral cameras, which can be used on unmanned aerial vehicles, has changed the local-scale monitoring. The UAV-based systems allow centimeter spatial resolution, intra-field variability in agricultural landscapes, and also facilitate field-based ecological measurements with unprecedented

accuracy. Despite limited payload and battery life and complex calibration, UAV platforms deliver a necessary bridge between field spectroscopy and massive aerial survey [4,9,20,21].

Table 1 presents a comparison of exemplary hyperspectral platforms, such as spaceborne, airborne, and UAV systems, including their spectral range, spatial resolution, coverage, and common uses. The table facilitates the discussion of platform trade-offs by quantifying capabilities and constraints (e.g., the large coverage and small spatial resolution of satellites and the small coverage and large scale of UAVs). A direct comparison of such parameters allows the readers to comprehend how the choice of the platform affects the methodological decisions, as well as the practicality of monitoring various natural resources.

Table 1. Comparison of Hyperspectral Remote Sensing Platforms.

Platform/Mission	Type	Spectral Range (nm)	Bands	Spatial Resolution	Swath Width	Notable Strengths	Typical Applications
Airborne Visible/Infrared Imaging Spectrometer (AVIRIS) (USA)	Airborne	400–2,500	~224	4–20 m	~11 km	High spectral fidelity; long-term calibration record	Vegetation studies, mineral mapping, water quality
Hyperspectral Mapper (HyMap) (Commercial)	Airborne	450–2,500	~126	5–10 m	~3–5 km	High Signal-to-Noise Ratio (SNR); stable performance	Geology, soil mapping, biomass assessment
Environmental Mapping and Analysis Program (EnMAP) (Germany)	Satellite	420–2,450	244	30 m	30 km	High radiometric stability; environmental monitoring focus	Global vegetation, soils, water bodies
PRecursore IperSpettrale della Missione Applicativa (PRISMA) (Italy)	Satellite	400–2,500	239	30 m	30 km	Strong calibration; robust spectral range	Agriculture, geology, and environmental applications
DLR Earth Sensing Imaging Spectrometer (DESI) (ISS)	Satellite	400–1,000	235	30 m	30 km	Flexible tasking; high revisit	Vegetation dynamics, coastal monitoring
Unmanned Aerial Vehicle (UAV) Hyperspectral Sensors (e.g., Cubert, Headwall)	UAV	Varies by model	50–200+	2–20 cm	Scene dependent	Ultra-high spatial resolution; flexible deployment	Precision agriculture, wetland mapping, canopy studies

2.4. Key Sensor Characteristics

The utility of hyperspectral data depends on several basic sensor properties that define how this type of data can be used in specific applications. The instrument can resolve narrow absorption bands related to biological or mineralogical processes, and this is determined by spectral resolution and bandwidth. Smaller bands tend to yield better discriminative ability, but they demand more signal-to-noise ratio to be faithful, particularly in dark or low-reflection targets like water bodies or dense forests. The spatial resolution affects the extent to which elements of hetero-

geneous land cover can be resolved; the finer the sensor, the higher the capacity of the sensor to capture fine-scale variation at the expense of a larger data volume and within-scene illumination effects. The stability and accuracy of recorded reflectance values are determined by radiometric sensitivity and are essential in activities where quantitative retrievals of biophysical parameters are being made. Additional characteristics, including swath width, frequency of coverage, and technology of the detector (including push-broom imaging systems), have an impact on continuity of the data, utility at the time of operation, and compatibility with other related data sets. The combination of these traits

is a crucial aspect to consider when choosing the right hyperspectral sensors and creating a workflow designed to meet a particular goal of environmental monitoring^[9,22].

2.5. Preprocessing and Calibration Workflows

Hyperspectral data before interpretation to obtain scientific information needs to go through a set of preprocessing procedures that aim at correcting sensor artifacts, atmospheric effects, and geometric distortions. Radiometric calibration transforms raw sensor data to physical values of radiance, using calibration coefficients calculated in a lab and in-flight corrections. The atmospheric correction is then used to remove the effect of scattering and absorption of gases and aerosols, which creates surface reflectance values that are similar over time and space. This step is especially important in those applications where fine spectral features should be obtained. Geometric correction is used to provide the correct spatial resolution and consider the platform movements, viewing geometry, and distortions due to terrain to enable the combination of hyperspectral data with other remote sensing data or geographic information systems. Spectral signs are made clearer and interpretable with noise-minimizing methods like spectral smoothing, signal vs. noise separation transformations, etc. Lastly, cloud, shadow, or abnormal pixel detection and masking activities should be included to avoid cloud contamination of downstream activities. All these preprocessing workflows are the backbone on which strong hyperspectral analysis is supported and needed to draw credible information to aid in the management of natural resources^[8,9,23].

3. Methodological Advances in Hyperspectral Data Processing

The analytical power of hyperspectral remote sensing is due to the richness of spectral measurements, but it is also due to the sophisticated computational techniques that have been developed to help identify meaningful information in the high-dimensional, complex data. The latest advances in machine learning, spectral unmixing, dimensionality reduction and multi-sensor fusion have significantly increased the accuracy, scale and scope of hyperspectral analyses, making it possible to better incorporate

imaging spectroscopy in the running of natural resource management. With the increase in the use of hyperspectral sensors in the airborne, satellite, and UAV systems, these methodological advances are deemed to be critical in the transformation of crude imagery into practical scientific and environmental information^[24-26].

3.1. Spectral Unmixing and Sub-Pixel Analysis

The spectral unmixing is still one of the basic elements of hyperspectral data analysis, and this method is especially important in heterogeneous landscapes where single pixels frequently have blends of several different materials. The general aim is to break down the reflectance spectrum of each pixel into individual endmembers and the abundance fractions of the endmembers. The traditional linear spectral unmixing methods are based on the fact that reflectance is a weighted sum of endmember signatures, and provide a physically interpretable solution that is both computationally efficient. The techniques have found extensive application in monitoring vegetation, mineral mapping, and soil analysis, where species, mineral, or soil constituents mixtures often appear within a single pixel^[27,28].

Nonlinear interactions between materials are, however, common in natural environments (i.e., multiple scattering through vegetation canopies, shadowing due to rough terrain, intimate mixing in mineral soils) and are associated with non-linear mixing assumptions. In its turn, the idea of nonlinear unmixing has become widespread, which involves the use of radiative transfer modeling, kernel-based, or neural network architectures to include more complex light-material interactions. The techniques enhance precision in the difficult scenes, including dense forests, heterogeneous farmlands or coral reefs, or worn geological formations. The fact that hybrid methods have been developed based on the integration of physical models and data-driven algorithms has helped to even strengthen the robustness of the unmixing workflows, allowing researchers to access compositional information in even broader environmental constraints. With the current world moving towards advancing imaging spectroscopy to a global scale, spectral unmixing is still one of the cornerstone technologies in imaging spectroscopy to understand mixed pixels and extract sub-pixel information that can be used to monitor natural resources^[29,30].

3.2. Machine Learning and Deep Learning for Hyperspectral Data

Machine learning has taken centre stage in the analysis of hyperspectral data, as it can be used to model non-linear relationships, operate in high-dimensional data, and extrapolate to the conditions of the complex environment. Machine learning algorithms like support vector machines, random forests, and gradient boosting are conventional and have been used in classification and regression problems, having good performance with little training data and explainable feature significance. These techniques have worked in applications such as discrimination of crop type, forest mapping at the species level, retrieval of soil properties, and estimation of water quality^[31].

Recently, deep learning has transformed hyperspectral data processing, where automatic learning of spectral and spatial features is performed during the process of raw data processing. Convolutional neural networks have been particularly effective, one-dimensional networks to model spectral relationships, two-dimensional networks to model spatial context, and three-dimensional networks to model spectral and spatial context simultaneously. Such models are good for land-cover classification, anomaly detection, and spectral reconstruction. Besides, recurrent neural networks and attention-based transformer models are proving useful in learning long-range spectral dependencies and working with large-scale datasets with complicated patterns^[31,32].

Deep learning approaches, though, involve large amounts of training data, which is still a problem when hyperspectral applications are concerned. In an attempt to overcome this drawback, methods of transfer learning, semi-supervised learning, and synthetic data augmentation are being embraced. Moreover, the explainability of deep learning models is a dynamically developing field of investigation, since it is important to comprehend the spectral characteristics underlying the predictions in order to be scientifically acceptable and operationally applicable. All in all, machine learning and deep learning have greatly expanded the analytical power of hyperspectral remote sensing and made it much more accurate, automated, and able to be used in a wide range of environmental applications^[33].

3.3. Dimensionality Reduction and Feature Extraction

Hyperspectral data, which are typically represented by hundreds of spectral bands, are inherently high-dimensional, multicollinear, and noisy. The importance of dimensionality reduction methods in addressing these issues is to provide the most informative features and retain the underlying spectral-spatial structure. Principal component analysis and minimum noise fraction transformations continue to be popular classical techniques that are used to reduce redundancy and improve signal quality. These techniques are used to reduce the hyperspectral data to a small format that highlights the variance or signal-to-noise properties, which can be used as a pre-processing step before classification or unmixing^[34].

In addition to the linear methods, nonlinear dimensionality reduction algorithms like manifold learning have been of interest due to their capacity to learn complex, intrinsic data structures. Such algorithms as t-Distributed Stochastic Neighbor Embedding (t-SNE), Uniform Manifold Approximation and Projection (UMAP), and locally linear embedding may be used to either visualize or cluster hyperspectral data to lower-dimensional spaces that more effectively reflect nonlinear interconnections between spectral signatures. Simultaneously, machine-learning-based methods of feature extraction, especially the autoencoders and variational autoencoders, have shown good performance in learning concise spectral representations directly out of the data. These deep learning-based techniques not only reduce dimensionality, but are also useful in noise removal, anomaly detection, and spectral synthesis.

The reduction of dimensionality is crucial to enhance the efficiency of the computations, minimize overfitting, and increase the interpretability of the hyperspectral analyses. With the increasing sensor placement, the volume of data is increasing, so effective and powerful feature extraction methods will also always be part of the package to facilitate real-time and large-scale environmental monitoring^[9,22,35,36].

Table 2 provides an overview of the principal types of hyperspectral data processing methods, namely spectral unmixing, machine learning, deep learning, and dimensionality reduction techniques. In both methods, the bene-

fits, weaknesses, and common areas of use are indicated. It provides insight into the story by offering a brief, comparative view that complements the methodological discussion in Section 3.

Table 2. Overview of Major Hyperspectral Data Processing Techniques.

Method	Core Principle	Advantages	Limitations	Typical Applications
Linear Spectral Unmixing	Models pixel reflectance as a linear combination of endmembers	Interpretable; computationally efficient	Assumes linear mixing; limited in complex environments	Vegetation fraction mapping, soil composition
Nonlinear Spectral Unmixing	Accounts for nonlinear light-material interactions	Better accuracy in heterogeneous scenes	Computationally intensive; requires complex models	Forest canopies, minerals, corals
Principal Component Analysis (PCA)/Minimum Noise Fraction (MNF)	Reduces dimensionality by maximizing variance or Signal-to-Noise Ratio (SNR)	Efficient noise reduction; simplifies data	May lose subtle spectral features	Preprocessing, classification
Autoencoders/Deep Feature Extraction	Learns compact spectral-spatial representations	Captures nonlinear patterns; excellent compression	Requires large datasets; less interpretable	Classification, anomaly detection
Convolutional neural networks (CNNs) (1D, 2D, 3D)	Learns spectral and spatial features via convolution	High accuracy; handles mixed spectral-spatial info	Data-hungry; high computational cost	Land cover classification, stress detection
Transformers/Attention Models	Models long-range spectral dependencies	High performance; scalable	Still emerging for Hyperspectral Imaging (HSI); complex training	End-to-end classification, anomaly detection
Data Fusion Techniques	Integrates Hyperspectral Imaging (HSI) with Light Detection and Ranging (LiDAR), Synthetic Aperture Radar (SAR), or multispectral data	Enhances accuracy; complementary information	Requires careful preprocessing	Biomass estimation, soil moisture, coastal studies

3.4. Real-Time and Onboard Hyperspectral Data Processing

The advent of real-time hyperspectral analytics is indicative of a larger trend towards the high-speed assessment of the environment and prompt decision-making. Conventional workflows are based on the post-flight or post-acquisition work, which may lag behind the provision of the already demanded information about disaster response, precision farming, or early ecological stress. More recent developments in sensor miniaturization and embedded processors, and edge computing architectures, can now enable partial or complete data analysis to be done on aerial platforms, such as UAVs and small satellites.

Onboard processing eliminates the amount of data that needs to be downlinked by compressing or band-selecting the data, or by reclassifying the data in real-time. It also supports dynamic sensing policies whereby the platform varies its acquisition policies according to the sensed environmental situations. An example is that a UAV can change its route to target regions with signs of stress, or a satellite can ensure that it transmits data to the regions that have irregularities. To ensure real-time processing, light-

weight analytic models and effective algorithms should be developed to tradeoff between accuracy and computation limitations. Due to the trend toward more real-time application of imaging spectroscopy, onboard and near-real-time processing will become more central to facilitating quick environmental intelligence^[37].

3.5. Integration of Hyperspectral Data with Other Sensors

The combination of multiple sensors is a current trend in modern Earth observation because various sensing modalities provide complementary information regarding the environment. Combined with hyperspectral data, lidar, synthetic aperture radar, and multispectral imagery, these offer structural, textural, or temporal data that improve the accuracy of analysis and expand the area of application. As an illustration, the hyperspectral and lidar data are used together to enable the concomitant description of the vegetation biochemistry and canopy structure to enhance estimates of biomass, forest health, and carbon stocks. On the same note, hyperspectral imagery, when combined with radar measurements, is better at retrieving the soil moisture,

surface roughness, and hydrological parameters, particularly on cloudy days or in highly vegetated areas ^[38].

Fusion of data also assists in surmounting such practical constraints as incompatible spatial resolution or lower temporal frequency of hyperspectral acquisitions. The simplest methods based on image stacking to the sophisticated machine learning-based fusion models can enable researchers to leverage the advantages of various sensors to come up with synergistic data that will enable more extensive environmental evaluation. With the arrival of multi-source, multi-band, and multi-polar in the next-generation satellite constellations, the multi-sensor integration will be even more important to scale up hyperspectral applications to regional and global scales ^[39].

3.6. Machine Learning versus Deep Learning Approaches

Both conventional machine learning (ML) and deep learning (DL) methods have also been extensively used in the analysis of hyperspectral data, although their strengths and weaknesses are not always highlighted. Support Vector Machines (SVMs), Random Forests (RFs), and k-Nearest Neighbors (k-NNs) are also widely used as ML techniques for classification and regression tasks with moderate-sized training datasets. Interpretability, computational efficiency, and resistance to overfitting of well-structured features are the general characteristics of this type of algorithm. Nevertheless, ML methods often rely on very carefully crafted features or dimensionality

reduction (e.g., PCA, MNF), which may limit their capacity to model nonlinear interactions in high-dimensional hyperspectral data.

Convolutional neural networks (CNNs), recurrent neural networks (RNNs), and transformer-based neural networks are examples of deep learning models with end-to-end learning properties that can automatically generate hierarchical spectral-spatial features from raw hyperspectral cubes. This enables DL to tackle complex tasks compared with standard ML, including sub-pixel categorization, anomaly identification, and the acquisition of collation information. However, deep learning has high data requirements (large labelled datasets), computational requirements (video Graphics Processing Unit (GPUs)), and hyperparameter search. Also, due to the black-box properties of DL models, interpretability is often a weakness, posing a severe drawback when making decisions in natural resource management.

On the whole, a critical evaluation demonstrates the complementary nature: in the short-term, interpretable analysis of small- to medium-scale studies, and in the long-term, high-dimensional data, when intricate spectral-spatial dynamics are to be represented, the ML methods continue to be used, and the DL methods are more acceptable. Hybrid ML-DL pipelines, or DL with feature selection, are considered an exciting direction in integrative methods to balance interpretability, computational efficiency, and accuracy ^[40,41]. A comparison of key characteristics of traditional machine learning and deep learning approaches is provided in **Table 3**.

Table 3. Comparison of traditional machine learning (ML) and deep learning (DL) across key aspects, including feature extraction, dataset requirements, computational demand, interpretability, typical applications, and representative algorithms.

Aspect	Traditional ML	Deep Learning (DL)	Ref.
Feature extraction	Manual/engineered	Automatic, hierarchical	Goodfellow et al. ^[42]
Dataset requirement	Moderate	Large labeled datasets	Southworth et al. ^[43]
Computational demand	Low to moderate	High (GPU recommended)	Southworth et al. ^[43]
Interpretability	High	Low (black-box)	Şahin et al. ^[44]
Best suited for	Small/medium-scale studies; interpretable mapping	Large-scale datasets; complex spectral-spatial patterns	Hossen et al. ^[45]
Example algorithms	SVM, RF, k-NN	CNN, RNN, Transformers	Haidarh et al. ^[40]

4. Applications in Sustainable Natural Resource Management

Hyperspectral remote sensing has become a revolutionary instrument in the management of natural resources in a sustainable manner because it has an unmatched capability of identifying subtle biochemical and biophysical characteristics of the materials on the surface of the earth. It has a fine spectral resolution allowing it to distinguish vegetation species, keep track of the state of the ecosystem, measure water and soil quality, and perform geological mapping. With increasing environmental issues and challenges in the world, the ability to produce correct, spatially explicit, and timely information has never been as important as it is today. The subsequent section outlines major areas in which hyperspectral technologies have made a major contribution to sustainability science and the mechanisms, opportunities, and implications of using the technologies ^[1,46,47].

4.1. Forest Ecosystems

Hyperspectral remote sensing usage in forests has increased at a high rate due to the necessity to track biodiversity, identify stressors affecting forest health, and measure biomass to keep a carbon count. Forests are extremely heterogeneous systems, which can consist of several species, age groups, and canopy forms that can be difficult to categorize using conventional multispectral data. Hyperspectral sensors, on the other hand, measure diagnostic absorption characteristics linked to pigments, lignin, water content, and leaf structural compounds and can differentiate among tree species with phenomenal accuracy. This allows the assessment of biodiversity, monitoring of ecosystem restoration, and mapping of invasive species to aid in informed conservation planning ^[48].

The ability of the hyperspectral data to identify the physiological stress even before it can be felt is equally important. Changes in spectral reflectance because of a shift in chlorophyll concentration, carotenoid ratios, water content of leaves, or photosynthetic efficiency enable early identification of drought stress, nutrient deficiencies, pest infestations, and disease outbreaks. This early-warning capability aids active management of the forests and

contributes to the prevention of massive loss of the forests. Moreover, hyperspectral imagery is at the forefront of the measurement of biomass and carbon stocks because it gives highly detailed information on canopy chemistry and structure. Hyperspectral measurements can be used in conjunction with lidar to make more precise and spatially distributed estimates about the amount of aboveground biomass, which can be useful in global climate mitigation efforts, including Reducing Emissions from Deforestation and Forest Degradation (REDD+) and forest carbon accounting models ^[49-51].

4.2. Water Resources

Hyperspectral remote sensing has established an exclusive role in the evaluation and monitoring of inland, coastal, and wetland water bodies, in which spectral information is usually confounded by a complicated conglomerate of dissolved and suspended compounds. Optical properties of water are very sensitive to variation in chlorophyll content, colored dissolved organic matter, turbidity, and mineral or organic particulates. Due to the small spectral resolution, hyperspectral sensors are capable of detecting characteristic absorption patterns with these constituents, with the help of which the precise water quality parameters can be restored. This can monitor eutrophication, harmful algae blooms, sediment plumes, and pollution events, which may have a significant adverse effect on the health of the ecosystem and human water security ^[52,53].

The hyperspectral monitoring is also very helpful to wetlands, which serve as biodiversity centers and sinks of carbon. Spectral signatures of wetland vegetation and moisture gradient conditions, and soil states can be mapped with high accuracy, providing new information about wetland structure, composition, and ecological functioning. Additionally, the hyperspectral data can be used to identify the impact of degradation processes like diminished vegetation vitality, hydrologic disturbance, or invasive species. The potential to resolve sediment dynamics and water constituent gradients is improved in riverine and coastal systems to improve the hydrological modeling, aid sediment budget estimates, and strategies to protect the coasts and manage the watershed ^[54].

4.3. Agriculture

Farming environments require constant surveillance in order to maintain sustainable productivity, resource input, and reduced environmental effects. Hyperspectral imaging is essential in giving essential information about crop physiology, soil characteristics, and yield potential at such minute detail that would not be possible with multispectral systems. Spectral properties of crops contain data on nutrient condition, pigment structure, water amount, and structure. These characteristics are sensitive to various stresses, including drought, nutrient deficiency, pest attack, or infection with a disease, meaning that hyperspectral sensors can detect early crop stresses many times earlier than the normal methods can. Consequently, hyperspectral is becoming a part of precision agriculture systems to support site-specific decisions in managing the site, to minimize chemical usage, increase water efficiency, and improve the health of crops.

Hyperspectral data are also very useful in soil evaluation as they record the changes in organic matter, clay minerals, moisture content, salinity, and contamination. This type of information is required in the analysis of soil fertility, land-use planning, and environmental risk assessment. In addition, spectral signatures are associated with plant biochemical and structural parameters at various stages of growth; thus, hyperspectral imagery can be used to make powerful yield estimation models. These models enable farmers and researchers to predict the production results, better resource use, and come up with adaptability measures in the face of changing climatic conditions, when combined with meteorological or phenological data ^[55,56].

4.4. Mineral and Energy Resources

Hyperspectral remote sensing has been identified as a vital instrument in the field of geological mapping and mineral exploration because it is capable of defining and distinguishing minerals based on their typical spectral absorption patterns. Numerous minerals are characterized by specific vibrational absorptions in the shortwave infrared region that allow mapping the lithological units, alteration zones, and mineral deposits that are structurally controlled in detail. This can greatly enhance the effectiveness of ex-

ploration since it does not involve a lot of sampling in the field, and also helps in narrowing down on areas that are of interest for further exploration ^[57].

In addition to exploration, hyperspectral imagery is useful in environmental surveillance that is linked to mining and energy extraction. It is able to discover the surface disturbances, map waste materials, and test the composition of tailings and heaps of spoils, which is useful in environmental compliance and rehabilitation programs. Hyperspectral data are used to detect stress on vegetation and hydrocarbon pollution in regions with petroleum extraction, which allows conducting an assessment of the environment in the shortest time possible. The combination of these applications helps to show the importance of hyperspectral imaging in resource development and environmental stewardship, which can be used to protect a more sustainable approach to the mineral and energy industries ^[58,59].

4.5. Coastal and Marine Ecosystems

Coastal and marine systems are very dynamic systems with the capacity to sustain biodiversity, fisheries, and coastal preservation activities. Hyperspectral remote sensing has some distinct benefits in the monitoring of such environments, given its capacity to capture a slight spectral difference that is related to benthic habitats, water column components, and shoreline characteristics. High-resolution measurements of the hyperspectral reflectance of coral reef environments can be used to detect variations in pigment cell makeup, symbiotic levels, and skeletal traits, allowing coral bleaching (along with other manifestations of coral stress) to be sensitively detected. This accuracy is essential for the protection of reefs and also in the consequences of climate change, pollution, and overfishing ^[58].

Mappings in the seagrass beds, macroalgae, and other benthic habitats in coastal areas using hyperspectral imaging enable an insight into ecosystem structure and well-being. Such environments tend to be spectrally elaborate and spatially heterogeneous, and therefore hyperspectral methods are particularly useful. More so, the hyperspectral data are used to monitor the erosion processes, sedimentation, and quality gradients of water bodies, which are critical in integrated coastal zone management. The capacity to observe small-scale environmental vari-

ations can be applied to make decisions on habitat conservation and coastal rehabilitation actions, and climate change ^[59]. A synthesized overview of key hyperspectral indicators, primary applications, example outcomes, and major challenges across different environmental domains is presented in **Table 4**.

Table 4. Applications of Hyperspectral Remote Sensing Across Environmental Domains.

Environmental Domain	Key Spectral Indicators	Primary Applications	Example Outcomes	Major Challenges
Forests	Chlorophyll, red-edge, water absorption features	Species mapping, stress detection, biomass estimation	Early pest detection; improved carbon stock models	Shadow effects, canopy complexity
Water Resources	Absorption by chlorophyll-a, Colored Dissolved Organic Matter (CDOM), suspended sediments	Water quality assessment, Harmful Algal Blooms (HAB) detection, wetland monitoring	Accurate constituent retrieval; sediment tracking	Atmospheric and sun glint effects
Agriculture	Pigment composition, nutrient-sensitive bands, canopy structure	Precision farming, soil mapping, yield forecasting	Early stress diagnosis; optimized inputs	High variability in crop types and conditions
Minerals and Geology	Clay, carbonate, iron-oxide absorption bands	Mineral exploration, lithological mapping	Alteration zone identification; cost-effective exploration	Nonlinear mixing, weathering effects
Coastal & Marine	Benthic reflectance, algal pigments, suspended matter	Coral reef health, seagrass mapping, coastal erosion	Early bleaching detection; habitat mapping	Water column correction, turbidity

Hyperspectral remote sensing (HSRS) is a revolutionary technology in the management and monitoring of natural resources, providing the most spectral information with the ability to precisely describe vegetation, soils, water, and minerals. Although methodological developments and applications were discussed in the previous sections, it was found that the practical usefulness of the developments is best demonstrated with real-life case studies. In this section, the main examples provided are those in China, the Netherlands, and Germany, emphasizing the methodological rigor, sources of data, assessment strategies, and lessons learned. Such cases are not just analyzed descriptively but critically, highlighting the strengths, limitations, as well as trade-offs that are involved with each platform and method of analysis ^[60,61].

5. Case Studies and Comparative Analysis of Hyperspectral Remote Sensing Applications

5.1. China: Forest Species Mapping and Disease Monitoring

The use of airborne hyperspectral imagery has been utilized to identify tree species and monitor early symptoms of tree disease stress in the subtropical forests in Hubei and Sichuan Provinces ^[62,63]. Compact Airborne Spectrographic Imagers (CASI/SASI) were used to obtain the

imagery with a spatial resolution of 1–2 m and a spectral range between 400–1,000 nm. The classification models were successfully validated using ground-truth data, which were gathered by means of comprehensive field plots. Both the classic machine learning, such as Random Forests (RF), and the deep learning method, namely one-dimensional Convolutional neural networks (1D-CNN), were used on the dataset. Before analyzing the atmospheric effects, geometric registration and denoising of the images were performed. To reduce features, principal component analysis and spectral indices were applied to reduce the number of features, including the normalized difference vegetation index (NDVI) and red-edge position, to improve the performance of the model.

Those results showed that CNNs performed better than RF classifiers and reached a general accuracy of 92% against 85% in the latter, with the corresponding kappa coefficients of 0.89 and 0.81, respectively. This is owed to the fact that deep learning is able to develop intricate spectral-spatial interactions in heterogeneous forests, especially in mixed-species plots. Nevertheless, the large-scale computational resources and large amounts of labeled data that the deep learning models demanded highlight the persistence of relevance of the classical machine learning strategies in which intelligibility and computational efficiency are paramount criteria. More importantly, multi-platform data acquisition is complementary, where there is rapid validation and fine-scale mapping through

the integration of the UAV-based imagery^[64,65].

5.2. The Netherlands: UAV-Based Crop Stress Assessment

Hyperspectral imaging by UAVs has been used in Flevoland, an intensively agricultural area in the Netherlands, in the detection of early signs of crop stress and chlorophyll content in wheat fields. The use of hyperspectral sensors on UAVs was a source of ultra-high spatial resolution imagery with a ground sampling distance of about 5 cm spanning the spectral range of 400–1000 nm. There was supplementary contextual validation through the application of Sentinel-2 multispectral imagery. Preprocessing of the acquired data was done using radiometric and atmospheric correction by the use of empirical line calibration methods^[66].

The Partial Least Squares Regression (PLSR) and Convolutional Neural Network (CNN) models were used to forecast chlorophyll content and identify early stress of disease. Cross-validation with field-based Soil Plant Analysis Development (SPAD) measurements showed that CNN models attained higher consistency in performance than PLSR, with a coefficient of determination (R^2) of 0.86 and a root mean square error (RMSE) of 1.3 SPAD units versus 1.9 SPAD units. These findings emphasize the ability of UAV-based hyperspectral sensors to display finer-scale variation in crop condition, which is frequently not well seen in the coarser-resolution satellite images. The case provides a strong indication of the importance of platform selection and spatial resolution to precision agriculture and how UAVs can be used to supplement spaceborne sensors to take actionable steps for early warning purposes^[67–69].

5.3. Germany: Coastal Water Quality Monitoring

Hyperspectral satellite imagery has also been used to assess the quality of water in the Baltic Sea coast in Germany, particularly the chlorophyll a level, phycocyanin, and suspended solids. The PRISMA and EnMAP spaceborne sensors had a spatial resolution of 30 m and a spectral range of 400–2500 nm. Atmospheric correction was done to the imagery through Atmospheric Correction for

OLI ‘lite’ (ACOLITE), and the pixels that were cloudy and the pixels exhibiting sun glint were masked. In analytical methods, spectral unmixing was used with Support Vector Regression (SVR), which was calibrated and tested using in situ water quality measurements collected in 120 sampling sites during high spring bloom periods.

The estimates obtained with the satellite had coefficients of determination of 0.81 and 0.75 with respect to chlorophyll-a and suspended solids, respectively, and RMSE of 1.8 mg/m³ and 2.5 g/m³. Although space-based hyperspectral sensors can successfully monitor on a regional scale, their restriction of the spatial resolution can restrict the ability to detect small-scale structures like small coastal algal blooms or local turbidity plumes. The study shows the benefits of incorporating multi-platform data, i.e., UAV or airborne hyperspectral data, which can be used to complement satellite data to enhance spatial resolution and operational decision-making. Importantly, this case shows that although deep learning and spectral unmixing can improve the predictive quality, the methodological decisions should be determined by platform-specific limitations as well as the magnitude of monitoring^[70–72].

5.4. Comparative Analysis and Synthesis

A cross-case study indicates a number of general findings. Deep learning has a regular tendency to enhance classification and prediction accuracy of complex, high-dimensional hyperspectral data at the expense of interpretability and computational resources. The traditional machine learning applications are still useful in cases of moderately sized datasets and the necessity of model transparency. The spatial resolution and flexibility offered by UAV platforms allow detection of stress or disease in crops and vegetation almost instantly, and contrasts with airborne platforms in that the latter can give a resolution between coverage and spatial detail appropriate to a heterogeneous landscape. Spaceborne hyperspectral sensors cannot be ignored as far as monitoring the region and long-term change detection is concerned, but due to their coarser spatial resolution, the spaceborne sensors might miss small-scale phenomena. Combined UAV with airborne hyperspectral and satellite hyperspectral data are seen to be a crucial method that can be used to maximize the spatial resolution as well as

the coverage, and in this way, resource monitoring and management are enhanced [73,74].

Besides methodological appraisal, these case studies have valuable lessons. Airborne data in combination with deep learning was used in China to fine-grain out species in an intricate forest. UAV-based imagery was found to enhance precision agriculture interventions in the Netherlands because it was possible to identify subtle crop stress early. Much of the dynamics of the water quality on large scales was observed through spaceborne hyperspectral monitoring in Germany, but the high-resolution UAV data was required to integrate with the spaceborne data to achieve the local scales. Altogether, these illustrations

indicate that the technological advancements in the field of hyperspectral remote sensing are the ones that have the greatest effect when the methodological rigor, platform capabilities, and application specifics are congruent. **Table 5** provides a summary of the three international case studies presented in Section 5, presenting a direct comparison of the type of platform, spatial resolution, analytical techniques, measurement parameters, and central findings. It emphasizes that deep learning models are more accurate in complex forests, UAV-based imagery can offer early warning of crop stress, and space data can be useful when monitoring water quality at a regional level. And strengthens the lesson points of the case studies [75-77].

Table 5. Comparative summary of hyperspectral remote sensing case studies.

Case Study	Country	Platform	Spatial Resolution	Analytical Approach	Evaluation Metrics	Key Findings	Ref.
Forest species mapping and disease monitoring	China	Airborne (CASI/SASI)	1–2 m	Random Forest, 1D-CNN; PCA and spectral indices	Overall Accuracy: 85–92%; Kappa: 0.81–0.89	Deep learning captures complex spectral-spatial patterns; ML remains interpretable; UAV integration improves fine-scale mapping	Zhang et al., Shen and Cao [78,79]
Crop stress monitoring	Netherlands	UAV-based hyperspectral	5 cm	PLSR, CNN; calibrated with field SPAD measurements	R ² : 0.72–0.86; RMSE: 1.3–1.9 SPAD units	Ultra-high-resolution UAV imagery allows early stress detection; CNN outperforms regression for non-linear responses; complements satellite imagery	Chakhvashvili et al. [80]
Coastal water quality monitoring	Germany	Spaceborne (PRISMA, EnMAP)	30 m	Spectral unmixing, SVR; validated with in-situ measurements	R ² : 0.75–0.81; RMSE: 1.8–2.5 mg/m ³	Regional-scale monitoring effective; fine-scale features require UAV supplementation; platform choice affects spatial detail vs. coverage	van der Meij et al., Canicatti, Sudu et al. [81–83]

6. Challenges and Emerging Research Directions

Hyperspectral remote sensing, although potentially having obvious scientific and increasing operational importance, nevertheless encounters numerous technical, logistical, and conceptual challenges, which restrict its use in the sphere of natural resources management. These issues are based on the fact that hyperspectral data are high-dimensional, sensor-related restrictions, complexities of the environment and atmosphere, and institutional/socioeconomic barriers influencing the process of converting imagery to action. Simultaneously, the blistering development of computation, sensor technology, and artificial intelligence provides new possibilities to overcome these limitations. It is vital to know the challenges and the new research directions in order to lead the new generation of

hyperspectral applications in the context of global sustainability in the larger scope [1,84].

6.1. Data Volume, Computational Requirements, and Processing Bottlenecks

The amount of data that current sensors produce is one of the most persistent issues of hyperspectral remote sensing. Since hyperspectral images have hundreds of narrow bands, their size is large compared to multispectral datasets, resulting in large storage, transmission, and processing requirements. These demands are further increased when sensors develop higher spatial resolutions and increased time coverage. Ecosystem monitoring across continents or global areas of mineral mapping can easily surpass the processing capability of conventional computational infrastructures.

In addition, analysis of hyperspectral data can be

characterized by complicated preprocessing procedures, such as atmospheric correction, geometric alignment, noise elimination, and calibration, each of which needs computationally intensive algorithms. The downstream calculations, like spectral unmixing, feature-extraction, or deep learning-based classification, lead to further computational load increment. Though cloud computing and distributed processing models have already started to overcome these problems, further investigation is required to create more effective algorithms, compression methods, and real-time processing plans to be able to process hyperspectral data at operational levels ^[16,22].

6.2. Need for Standardized Spectral Libraries and Calibration Protocols

The fact that no single spectral library exists that is comprehensive, standardized, and capable of capturing the full variability of natural materials across different geographic locations, seasons, and environmental conditions is a significant impediment to the operationalization of hyperspectral technologies. Current spectral libraries tend to differ in acquisition protocols, illumination conditions, sensor properties, and pre-processing, and they are hard to compare or transfer models across datasets. This lack of consistency reduces the reproducibility of research and restricts the construction of powerful machine learning models that need huge and standard training sets.

Equally, disparity in sensor calibration, atmospheric correction algorithm, and data format pose problems in incorporating hyperspectral imaging across platforms. The compatibility between sensors across missions, as new missions are created with differing spectral specifications, is growing more significant. Studies of harmonized calibration standards, common reflectance retrieval protocols, and globally coordinated spectral databases will be important to allow more interoperability and the sustainability of hyperspectral measurements ^[85].

6.3. Atmospheric Influences, Environmental Variability, and Scene Complexity

It is also confirmed that the accuracy of hyperspectral measurements is highly dependent on atmospheric and environmental conditions during the acquisition. Spectral

signatures can be significantly distorted due to variations in aerosol loadings, humidity, solar angle, and cloud cover, especially in the visible and shortwave infrared areas. Although complex algorithms of atmospheric correction are available, they do not work equally well in all places, particularly where humidity is high, the topography is complicated, or the plant cover is thick. There are other difficulties in the coastal and water settings where light reflects off water surfaces, making the retrieval of signals difficult.

The complexity of hyperspectral analyses is also created by environmental heterogeneity. As an illustration, shadowing effects in the forest, anisotropic reflectance of crop canopies, and close mixing of minerals in soils may result in nonlinear spectral response and make it difficult to identify materials. It will be necessary to continue studying better radiative transfer models, machine learning methods that are physically informed, and methods of adaptive atmospheric correction to solve these problems and make the hyperspectral interpretations more reliable in different environments ^[86].

6.4. Sensor Interoperability, Temporal Consistency, and Multi-Platform Integration

With the increase in the number of hyperspectral missions, the need to maintain uniformity with the different sensors has become the issue of the highest emerging demand. The spectral resolution, band location, radiometric sensitivity, and viewing geometry of data differ; thus, it is challenging to compare data directly. The temporal scales required for long-term environmental monitoring demand that real environmental changes be tracked over time, and discrepancies between sensors may conceal true changes or make it difficult to reconcile past and present data.

Additionally, it is common to use hyperspectral imagery with other forms of data, like lidar, radar, or multispectral imagery, in order to gain more benefits with many management applications. Nevertheless, combining datasets of different spatial resolutions, geometries of acquisition, and frequencies of time demand complex fusion algorithms and proper validation. The studies of sensor harmonization, multi-resolution fusion algorithm, and cross-platform calibration structure are needed to provide a smooth integration of hyperspectral data into multi-sensor

Earth observation systems ^[87].

6.5. Socioeconomic, Operational, and Data Accessibility Barriers

Outside of technical constraints, there are various socioeconomic and operational obstacles that restrict the use of hyperspectral technology in sustainability applications. The large cost of acquisition, the scarcity of airborne systems, and the inability to access the data are some of the reasons that many areas, especially in developing nations, might not maximize the potential of hyperspectral. Although hyperspectral images can have the specialized skills necessary to process and interpret the data, even with available data, their use may be constrained by natural resource managers, conservation practitioners, or local authorities. Large-scale implementation is also impeded by institutional issues, such as the issue of privacy in precision agriculture, and the necessity of long-term capacity building.

The solution to these obstacles will involve easier access to open-source data, easy-to-use spectral analysis tools, and structures that place a higher emphasis on training and knowledge transfer. Hyperspectral technologies can also be more widely adopted in policy, conservation, and resource management situations with the help of operational guidelines that will fill the gap between scientific research and practical decision-making ^[88].

6.6. Emerging Frontiers in Hyperspectral Research and Technological Innovation

Nevertheless, these obstacles do not hold back the future of hyperspectral remote sensing, which is characterized by a breakneck pace of innovation and an increase in opportunities. The current development of sensor miniaturization and optical technology is allowing the creation of small hyperspectral systems that are great for UAVs, CubeSats, and even handheld devices, making them more accessible and providing more observations. New quantum sensing technologies and new detector architectures can work to enhance sensitivity and spectral resolution to allow new applications that have been hitherto restricted due to noise or atmospheric interference.

In parallel, the future of hyperspectral analysis is

expected to see a revolution come with artificial intelligence, through self-supervised learning, neural networks with physics information, and fundamental models that are able to generalize across/even between sensors and environments. These methods offer to significantly decrease the use of labeled data and enhance the interpretability and strength of hyperspectral models. Also, the incorporation of hyperspectral data into digital ecosystems, climate-sensitive agricultural systems, and biodiversity networks on the planet constitutes one of the promising prospects of predictive and real-time environmental evaluation ^[89-91].

In the future, the convergence of sensor technology, the development of computation, and interdisciplinary coordination will be a significant factor in achieving the full potential of hyperspectral remote sensing. These new areas of research point to a direction of having more scalable, accessible, and operational applications to aid in achieving global sustainability and decision-making within natural resource management.

7. Conclusions

Hyperspectral remote sensing has become an effective and multifaceted instrument that can revolutionize the manner in which natural resources can be tracked, controlled, and preserved. Hyperspectral imaging provides novel knowledge about terrestrial, aquatic, agricultural, geological, and coastal systems by measuring spectral spectra with high resolution and analysis of surface materials, giving an understanding of biochemical, structural, and compositional characteristics of samples of surface materials. The scope and accuracy of hyperspectral applications have changed significantly over the last ten years due to advances in sensor technology, data processing algorithms, machine learning and multi-sensor integration. The developments have brought about more accurate species discrimination in forests, preliminary identification of environmental stress in crops and ecosystems, deeper measurement of soil and water quality and more effective identification of mineral resources, all of which are fundamental elements of sustainable natural resource management.

Although these have been achieved, there has been a continued challenge in moving hyperspectral remote sensing research-based studies into existing applications

and even policy-relevant applications. Among the main challenges are the massive data rates produced by current sensors, the complexity of the preprocessing processes, the lack of standardization both between spectral libraries and between spectral calibration processes and technical challenges of atmospheric variability, sensor interoperability, and fusion between platforms. Also, socioeconomic and institutional restrictions continue to have an influence on the availability of data and the use of hyperspectral instruments, especially in areas that will not have the necessary technological resources or skills.

However, new technologies portend a bright future for imaging spectroscopy. The spaceborne missions of new generations, miniaturized UAV-based sensors, and quantum-enhanced sensors are expected to provide larger, more available, and higher quality hyperspectral datasets. Simultaneously, the research in the field of artificial intelligence has also transformed the analysis, as inventions such as physics-informed learning, self-supervised modeling, and large-scale spectral foundation models are now offering more efficient, interpretable, and scalable data analysis platforms. The advances will assist in closing the scientific capabilities/operational needs gap to assist in the development of real-time monitoring, early-reaction systems, and integrated environmental decision support tools.

In short, hyperspectral remote sensing is the leader of the new generation of Earth observation technology, with the necessary scientific capacity and operational flexibility that can meet the demands of the complex issue of the sustainability of natural resources. In continued cooperation and innovation by research and operational communities, hyperspectral imaging will assume an escalating importance in the development of global sustainability objectives- improving our capacity to track ecological transitions, wisely implement resources and create strong environmental systems that will be able to withstand future environmental challenges.

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Conflicts of Interest

The authors declare no conflict of interest.

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