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REVIEW

Pushing the Boundaries of Sustainability: Advances in Hyperspectral Remote Sensing for Ecosystem and Natural Resource Management

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ABSTRACT

Also known as imaging spectroscopy, hyperspectral remote sensing is becoming a key technology for ecosystem and natural resource management sustainability. Hyperspectral observations can be used to measure tens to hundreds of narrow bands of reflected radiation to resolve diagnostic absorption bands and spectral shape variations associated with vegetation pigments, water status of the canopy, biochemical composition, mineralogies, and organic matter of the soil, and water quality constituents of aquatic water. These abilities allow one to make a transition between the descriptive mapping and the functional monitoring, the anticipation of stress and disturbance early, and the more accurate attribution of environmental change. This summary encompasses improvements on the entire sensor-to-product pipeline, including field and UAV (Unmanned Aerial Vehicle) system platform developments, airborne campaign and spaceborne mission developments, calibration and analysis-ready preprocessing improvements, empirical learning methodology improvements, radiative transfer-based inversion method, spectral unmixing, deep learning, and hybrid physics-machine learning. We underline the increased importance of the combination of data with LiDAR (Light Detection and Ranging), SAR (Synthetic Aperture Radar), and thermal features aimed at decreasing the level of ambiguity and enhancing operational resilience. Applications based on decision are evaluated in terms of biodiversity and habitat evaluation, vegetation functionality and restoration, stress and disturbance, sustainable agricultural production, inland water quality and coastal water quality, land degradation and soil status, and environmental impact assessment. Inhibiting factors to operational adoption have always been perceived to be domain shift by region, season, and sensor, ground truth and validation, mixed pixels and scale

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mismatch, preprocessing sensitivities, and desirable uncertainty quantification and product output that is interpretable. We conclude with the scalability, sustainability, service priorities, such as harmonization standards, representative benchmarking, uncertainty-aware delivery, and co-design of stakeholders.

Keywords: Hyperspectral Remote Sensing; Imaging Spectroscopy; Ecosystem Monitoring; Data Fusion; Uncertainty Quantification

1. Introduction

The new frontier of ecology management and natural resource management is becoming sustainability as its solution and limitation [1]. Governments, industry, and communities are supposed to conserve biodiversity, sustain ecosystem services, water and food security, and minimize environmental hazards, and at the same time facilitate economic growth. These conflicting needs are playing out against a growing climate change, deepening regimes of disturbance (e.g., droughts, wildfires, storms), and speedy land-use changes. Here, the critical question is not whether we can see environmental change but whether we can see it in time, whether we can see it on an adequate scale, and whether we can see it with adequate diagnostic capability so as to act on it. Environmental intelligence that is timely, spatially explicit, repeatable, and interpretable is necessary to manage effectively and be able to distinguish between degradation and the natural variability, and where intervention has the most benefit is needed [2,3].

Remote sensing has traditionally provided an avenue to broad-area monitoring, but the majority of the products of operations have remained confined to coarse thematic classes or structural proxies. Multispectral imagery has revolutionized land cover mapping and vegetation indices, and radar and LiDAR have empowered our ability to measure the structure, moisture, and biomass [4]. Nonetheless, variables other than the structural have increasingly become important to the sustainability-related decision-making: leaf and canopy chemistry, the water status of plants, nutrient processes, soil organic matter, mineralogy in relation to land degradation or extraction effects, and water constituents of eutrophication and harmful algal blooms. These parameters tend to appear as information-rich but fine absorption and reflectance patterns that cannot be separated when using a limited number of far-between multispectral bands. Consequently, the managers are often compelled to make decisions based on half-baked diagnostics and rely on the late-stage indicators (e.g., canopy browning, visible algal scums, or erosion scars) instead of the early warning signs that would allow losses to be avoided.

Hyperspectral remote sensing, also called imaging spectroscopy, is an approach that directly fills this diagnostic gap by recording reflected (and sometimes emitted) radiance in tens or hundreds of narrow, non-filtered spectral bands [5]. This spectral richness allows the biochemical and biophysical properties that are hard or impossible to estimate robustly using multispectral data to be retrieved. In the case of terrestrial ecosystems, hyperspectral sensors can measure pigment structure and concentration, canopy water content, dry matter characteristic of fuel properties, and nutrient and stress physiology proxies. Hyper spectral observation can be used in the case of soils and exposed surfaces to determine the presence of organic matter, moisture, salinity signs, and mineral composition related to degradation processes. Imaging spectroscopy can measure vital water quality parameters, including chlorophyll a, colored dissolved organic matter (CDOM), and suspended sediments, and assist in detecting cyanobacteria blooms during favorable conditions [6]. These capabilities are in line with sustainability priorities: conservation of biodiversity, reduction of drought and fire hazards, sustainable agriculture, watershed protection, verification of restoration, and monitoring compliance with resource mining and land-use effects.

Notably, hyperspectral sensing does not require more bands. It is a turn away from descriptive mapping, in favor of a more mechanistic inference: what is there? What is the condition of it, why, and how is it changing? Such change is especially topical in management environments where the cost of interventions is high and needs to be justified: the distribution of scarce resources for restorations, fuel treatments, changes in agricultural supplies, warming and warning messages to water resources. Hyperspectral products that are combined with uncertainty information and based on phys-

ical insights could help to make defensible decisions and transparent reporting, such as monitoring, reporting, and verification (MRV) processes and sustainability metrics based on ecosystem services and policy objectives [7].

The timing is also critical. Hyperspectral remote sensing is experiencing a new phase (i), which combines an ever-growing platform ecosystem, including field spectrometers, unmanned aerial vehicles (UAVs), air campaigns, and multi-orbiter missions; (ii) better radiometric calibration, atmospheric correction, and cross-sensor harmonization, resulting in multi-site and multi-temporal analysis becoming increasingly practical; (iii) significant improvements in computation and algorithms, especially machine learning (ML), deep learning (DL), and more physically-based hybrid methods that can utilize high-dimensional spectra at a large scale. Meanwhile, data fusion has come to play an important role in operational monitoring. A combination of hyperspectral images with LiDAR (structure), radar (moisture and all-weather sensitivity), and thermal data (canopy temperature and evapotranspiration proxies) may make it more robust, less ambiguous, and allow describing the ecosystem as a whole [8]. These are convergent trends that are currently propelling imaging spectroscopy out of its limited research use and into decision-relevant agency and practitioner products.

With this momentum, it does not just happen to translate advances in hyperspectral into sustainability. The attributes of hyperspectral data that enable its effectiveness, high dimensionality, sensitivity to atmospheric and illumination conditions, and multifaceted interaction of canopy structure, background soil, and the viewing geometry are the same factors that impede operationalization [9]. Mixed pixels still pose a cardinal problem with the heterogeneous landscape, especially when the scale of ecological features or management units outstrips the spatial resolution. Transferability Retrieval models can be limited to transferability: algorithms that have been trained or calibrated in a single biome, season, or sensor configuration can be poor elsewhere because of domain shift and phenological variation. Ground truth information that is vital in calibration and validation is costly to gather, not uniformly considered, and often not similar. Also, uncertainties caused by preprocessing (e.g., atmospheric correction, bidirectional reflectance distribution function (BRDF)/topographic effects, etc.) will propagate through the models in a manner that is hard to diagnose without systematic QA/QC. To decision-makers, these technical complexities may be represented by low confidence, low uptake, or products that are not easy to interpret and fit into the existing workflows.

Such issues drive one overall point of this review: the sustainability effects of hyperspectral remote sensing rely not on individual advances but on the wholeness of the entire sensor-to-decision chain. A high-performing retrieval model is not adequate when the calibration is unstable, there is preprocessing bias, non-representative validation, or there is no communication of uncertainty in a decision-relevant way. On the other hand, small improvements made at various levels of sensors harmonization, generation of analysis-ready data, powerful modeling, fusion, and uncertainty quantification can make reliable products that the agencies can trust and operationalize. In this sense, imaging spectroscopy has to be judged based not only on predictive accuracy of controlled research, but also on robustness across space and time, transparency, reproducibility, and suitability to the needs of management [10].

In this regard, this review summarizes recent developments in hyperspectral remote sensing using the sustainability and management perspective [4,11]. Our applications of interest are in fields associated with ecosystem and natural resource applications where the imaging spectroscopy can give quantifiable goodness: biodiversity and habitat analysis; vegetation trait mapping and ecosystem behavior; environmental early warning of stress and disturbance and recovery; sustainable agricultural production at field-to-watershed scales; inland and coastal water quality measurement; soil status and land degradation; and environmental impact evaluation concerning resource extraction and land-use change. Instead of focusing on these domains as separate collections of case studies, we will highlight the common methodological basis and operational bottlenecks that dictate whether hyperspectral products could be deployed to any degree of reliability.

The review is organized into six sections. Section 2 introduces the spectral and radiative transfer fundamentals that underpin ecosystem inference and clarifies why certain biochemical and biophysical variables are spectrally observable. Section 3 reframes the field around an end-to-end sensor-to-product pipeline, spanning platforms, calibration and preprocessing, feature representations, retrieval and unmixing methods, deep learning and hybrid models, data fusion strate-

gies, and uncertainty quantification. Section 4 connects these methodological advances to decision-centered applications, highlighting the link between management questions, hyperspectral observables, validation practices, and operational pathways. Section 5 consolidates key gaps and future directions, with particular attention to transferability, ground truth constraints, mixed pixels, preprocessing sensitivities, trustworthy AI, and the emerging potential of self-supervised and physics-informed approaches. Section 6 concludes with a practical synthesis of what is ready for operational adoption, what remains research-grade, and what investments in data, methods, standards, and stakeholder co-design are most likely to convert hyperspectral innovation into sustainability outcomes. **Figure 1** summarizes the end-to-end logic of this review, linking sustainability drivers and management information needs to hyperspectral observables, modelling/fusion pathways, and decision-ready products, with validation and uncertainty as cross-cutting requirements [4,12].

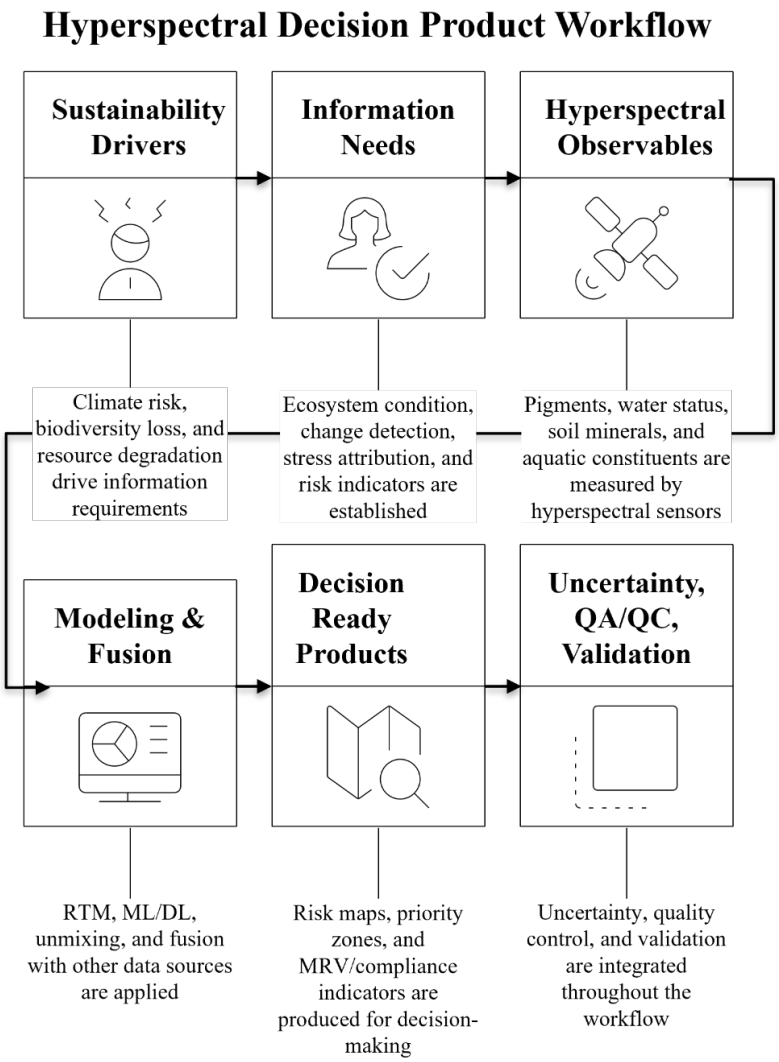

Figure 1. Conceptual Framework Linking Sustainability Challenges to Hyperspectral Decision Products.

Note: Theoretical model of how questions of sustainability-driven management (biodiversity conservation, water security, land degradation, compliance monitoring) can be converted into information requirements, hyperspectral observables, modeling directions, and decision-ready outputs. The quantification of uncertainty and quality assurance are demonstrated as the cross-cutting elements along the pipeline.

By centering sustainability use cases and emphasizing the full chain from spectra to decisions, this article aims to help researchers prioritize developments that matter for real-world deployment, and to help practitioners understand what hyperspectral remote sensing can deliver today, what it may deliver soon, and what conditions are necessary for its responsible and effective use in ecosystem and natural resource management.

2. Fundamentals of Hyperspectral Remote Sensing for Ecosystems and Natural Resources

Hyperspectral remote sensing, often termed imaging spectroscopy, measures reflected (and in some cases emitted) radiation in tens to hundreds of narrow, contiguous spectral bands [13]. The defining advantage of this approach is that it resolves diagnostic absorption features and subtle changes in spectral shape that are directly linked to chemical composition, water content, and physiological status of vegetation, soils, and aquatic systems. Because ecosystem processes are mediated by biochemical and biophysical properties rather than by land cover classes alone, hyperspectral data provide a pathway from descriptive mapping toward functional characterization. At the same time, the information content of hyperspectral imagery is inseparable from the physics of radiative transfer, the constraints imposed by sensor design, and the complexity of heterogeneous natural scenes. This section summarizes the spectral foundations that underpin ecosystem inference, clarifies which ecological variables are optically observable and why, and outlines the main scaling and ambiguity issues that must be recognized before moving from spectra to decision-relevant products.

2.1. Radiative Transfer Foundations and the Measurement Chain

The signal recorded by a hyperspectral sensor is the outcome of a coupled system involving solar illumination, atmospheric transmission, surface–atmosphere interactions, and sensor response [14]. For most ecosystem applications in the visible to shortwave infrared range, the fundamental quantity of interest is surface reflectance, which describes the fraction of incident radiation reflected by the surface as a function of wavelength. The pathway from at-sensor radiance to surface reflectance is nontrivial because radiance includes contributions from atmospheric scattering and absorption, adjacency effects from nearby bright targets, and angular dependencies associated with bidirectional reflectance distribution function (BRDF) behavior. These influences are wavelength-dependent and can be large enough to mimic or mask the spectral features used for biochemical retrievals, particularly in the blue region where scattering is strong and in spectral intervals dominated by atmospheric water vapor.

Canopy reflectances of terrestrial scenes combine a variety of elements, such as the optical properties of the leaf, the structure of the canopy, soil or understory reflectance as a background, and shadowing [15]. The pigments and water absorb light at the leaf level in a structural environment where multiple scattering of leaves, branches, and gaps determines the size and form of the reflected spectrum. As a result, biochemical change may exhibit a different appearance based on canopy architecture, distribution of leaf angle, clumping, and illumination geometry. Topographic effects are another phenomenon that is designed to change the relative reflectance of the surface in rough or piecemeal terrain, and this is in spite of the fact that surface properties remain constant. These problems encourage the popularity of physically-based radiative transfer models, BRDF corrections, and special consideration of the viewing geometry in hyperspectral studies aimed at ecological interpretation.

The remote sensing of water bodies presents extra complexity due to the fact that the signal measured is usually a comparatively small water-leaving signal relative to the radiance of the atmosphere path, at the visible wavelengths. Isolating the water-leaving reflectance and relating it to intrinsic optical characteristics controlled by phytoplankton pigments, dissolved organic matter, and suspended particles makes the radiative transfer problem one of isolating the water-leaving reflectance. Further, there is a bottom-reflectance term with optically shallow waters and benthic habitats, which is determined by substrate type and depth and leads to a coupled inversion solution. This means that hyperspectral aquatic applications often demand specialized atmospheric correction, thorough quality screening, and bio-optical modeling procedures unrelated to terrestrial operations [16,17].

2.2. Spectral Observables and Diagnostic Features in Ecosystems

The usefulness of hyperspectral imagery is that it is capable of resolving fine details of absorption and continuum shape variations, which are attributed to individual materials or physiological conditions [18]. The visible part of the vegetation has a high absorption of chlorophylls and accessory pigments, and allows one to make conclusions about the photosynthetic capacity and the pigment modifications in response to stress. The region where red absorption is

replaced by high near-infrared reflectance, commonly referred to as the red-edge region, is sensitive to chlorophyll concentration and canopy structure; the location and shape of this change can be measured more accurately using hyperspectral samples of the red-edge than in multispectral data. Multiple scattering in the near-infrared is hegemonic in leaf internal structure and canopy structure, and it is educative of structural properties, as well as susceptible to the effects of shadowing and background. Water absorption bands and cellulose, lignin, proteins, and other biochemical constituents' features are present in the infrared on the shortwave, which gives us a peep hole into the water status of the plant, the content of its dry matter, and other characteristics related to fuel moisture and decomposition processes.

The most important diagnostic wavelength bands underlying ecosystem inference by imaging spectroscopy are outlined in **Figure 2**, which include the pigment absorption and red-edge in vegetation, mineral and moisture-based absorptions of soils, and constituent-generated optical signatures in water [19].

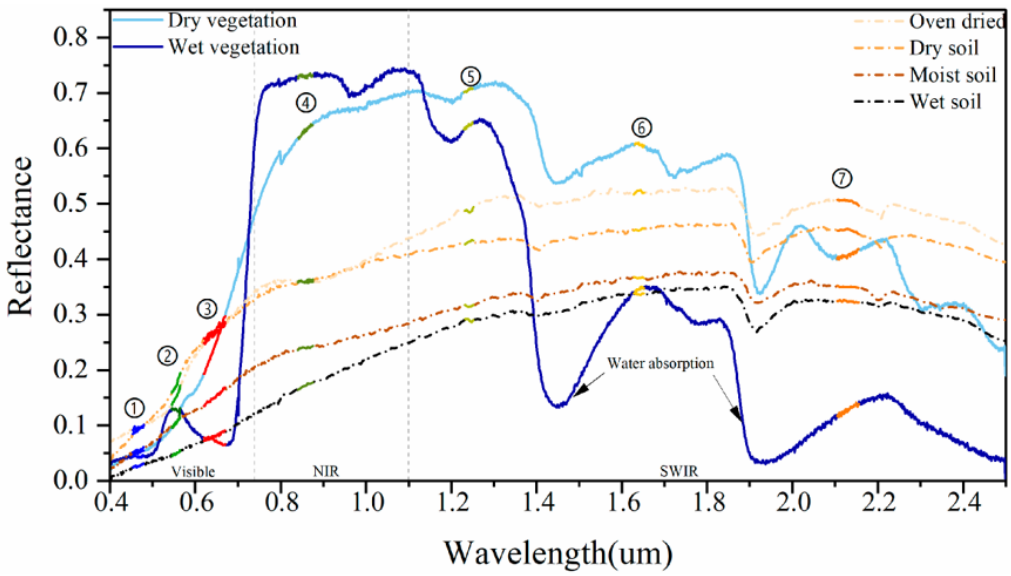

Figure 2. Spectral Foundations and Diagnostic Wavelength Features of Ecosystems.

Note: Schematic reflectance spectra illustrating key spectral characteristics of vegetation, soil, and aquatic ecosystems, where major features include pigment absorption in the visible regions 1–7 (Blue: 453–479 nm, Green: 545–565 nm, Red: 620–670 nm), the red-edge transition, strong structural scattering in the near-infrared region (NIR: 841–875 nm), and absorption features in the shortwave infrared regions (SWIR1: 1230–1250 nm, SWIR2: 1628–1652 nm, and SWIR3: 2105–2155 nm) associated with water content, dry matter, minerals, and organic compounds [19].

The spectral behavior of soils and bare surfaces is determined by mineralogy, organic matter, moisture, and the roughness of the surface. Hyperspectral sensors can distinguish among soil types and make inferences concerning weathering or degradation processes by measuring the diagnostic absorptions in the visible to shortwave infrared in iron oxides, clay minerals, carbonates, and others. Organic matter of soil is likely to darken the spectrum and change its form, whereas moisture adds strong absorptions, which may overwhelm the shortwave infrared and confuse mineral retrieval unless explicitly taken into account. Since soils tend to constitute the underlying signal in the context of partial canopy cover, the study of soil spectral differences is also significant to vegetation retrievals in sparse ecosystems and agriculture [20].

Hyperspectral sensors are better at isolating spectral signatures of chlorophyll a, colored dissolved organic matter (CDOM), and suspended particulate matter in inland and coastal waters than are broadband sensors, owing to overlapping spectral responses of these constituents [21]. Narrowband sampling allows one to better characterize the absorption peaks and scattering slopes, which are essential in the difference between phytoplankton blooms and sediment-based turbidity, and in tracing the dynamics of CDOM attributable to watershed inputs. Hyperspectral data may, in other instances, be used to carry out discrimination among algal functional types, including cyanobacteria, in instances where pigment-related characteristics are discernible and reliable atmospheric correction. In optically complex waters, however, separability of constituents is highly determined by

the ranges of concentrations, particle size distributions, and relative dominance of the absorption and scattering mechanisms.

In both terrestrial and aquatic environments, spectral features can be understood in a way contingent on the difference between observable and inferential features [22]. Other variables, like pigment absorption characteristics or water absorption bands, are directly represented in the spectrum. Other, e.g., leaf nitrogen or photosynthetic efficiency, can be estimated only indirectly by correlation with optically active constituents, or by trait syndromes that change in a systematic species-by-species or stress-by-stress fashion. This difference is essential to applications in sustainability since strong transfer between sites and seasons is more probable when the retrievals are based on physically articulated features and are not based on context-specific correlations.

2.3. Spatial Scale, Mixed Pixels, and Ecological Heterogeneity

Ecosystems are intrinsically heterogeneous, and the spatial resolution of hyperspectral imagery often does not match the scale of ecological features or management units [23]. Even at fine airborne or UAV resolutions, individual pixels may mix sunlit leaves, shaded leaves, soil, litter, and understory vegetation. At coarser satellite resolutions, mixing becomes the norm rather than the exception, particularly in fragmented landscapes, riparian corridors, savannas, and urban–ecological interfaces. Mixed pixels complicate interpretation because the observed spectrum is a composite of multiple materials whose relative contributions vary with illumination and viewing geometry.

Not only is thematic purity lost, but retrieved biophysical and biochemical properties are also ambiguous due to the effects of mixing. As an example, a decrease in canopy reflectance in the near-infrared can indicate structural change, a rise in the proportion of shade in the canopy, or more soil exposure than a physiological change. Likewise, infrared characteristics of shortwaves related to canopy water may be washed out by bright soils or increased by the viewing conditions, with accentuated components in the shade. Adjacency effects due to bright land surfaces and intermittent contributions of the bottom in aquatic environments may create bias during the retrieval of the constituents. These facts render spectral unmixing and physically based modeling to be core to hyperspectral ecosystem science, particularly when there is a need to generate spatially comparable indicators to aid management [16,24].

Scaling is also related to time dynamics. Phenology alters the biochemical and structural condition of vegetation to such an extent that it is sometimes surpassed by the intensity of stress signals. Change in pigmentation, leaf water, and canopy structure across seasons may be the major source of spectral variability, i.e., stress sensing and trend analysis need an explicit phenological context, and multi-temporal observations may be advantageous. To use it in the context of sustainability (like early warning), however, it would be necessary that abnormal departures be differentiated by the expected seasonal trends, and not just the single-date threshold [25].

2.4. Signal-to-Noise, Spectral Resolution, and Information Trade-Offs

The hyperspectral sensors are associated with basic trade-offs of spectral resolution, spatial resolution, temporal revisit, the width of the swath, and signal-to-noise ratio (SNR). Smaller bands enhance the capability to separate absorption features at the cost of the amount of photons per band, which may reduce SNR, especially in applications like low-reflectance targets, like water, dense forests in the blue band, or shaded terrain. In situations with low SNR, subtle spectral features may be distorted and retrieval accuracy decreased, particularly with biochemical parameters that express optically weakly. Spatial resolution has a relationship with SNR in that smaller pixels have fewer photons and are more sensitive to georegistration errors and in-pixel heterogeneity. Temporal resolution has effects on SNR and coverage since larger swaths and higher revisit frequency are usually at the cost of optical throughput or sampling plan [26].

These instrument-level constraints shape what is realistically observable in operational contexts. A retrieval method that performs well on high-SNR airborne data may fail when applied to noisier satellite data unless it is adapted to account for bandpass differences, SNR limitations, and calibration uncertainties. Conversely, retrievals based on robust, strongly expressed features may transfer well across platforms even when resolution and noise characteristics differ. For sustainability-focused monitoring, these considerations suggest that product design should start from the

intersection of ecological relevance and sensor capability, rather than from the availability of an algorithm alone [27].

2.5. Atmospheric, Angular, and Topographic Effects as Confounders

The sensitivity of hyperspectral data to narrow spectral features makes them particularly vulnerable to confounding effects introduced by the atmosphere and observation geometry [14,28]. Atmospheric water vapor absorption can overlap with surface water features in the shortwave infrared, and variable aerosols can alter spectral slopes in the visible, affecting pigment-related analyses. Adjacency effects, in which scattered light from nearby bright targets contaminates the radiance measured over darker targets, can be pronounced in heterogeneous landscapes and along shorelines. BRDF effects arise because natural surfaces are anisotropic reflectors; changes in solar and sensor geometry can produce spectral changes that are not related to surface composition. In mountainous terrain, topographic shading and varying illumination angles create spatial patterns in reflectance that can dominate the signal if not corrected.

From an ecosystem management perspective, these confounders matter because they can generate false trends or mask true changes, undermining trust in derived indicators [29]. Robust applications, therefore, require a combination of careful preprocessing, acquisition planning where possible, and modeling approaches that either correct for or are resilient to these effects. The need to manage confounding variability also underscores why uncertainty quantification and quality flags are not optional add-ons but prerequisites for decision-ready hyperspectral products.

2.6. From Spectral Information to Ecological Meaning

Interpreting hyperspectral observations in ecological terms requires connecting optically expressed properties to ecosystem processes and management objectives [30]. In many cases, hyperspectral data provide access to functional traits that mediate ecosystem responses to climate and disturbance, such as water status, pigment composition, and structural characteristics linked to productivity and resilience. Trait-based perspectives are increasingly used to bridge scales, because traits provide a common currency across species and communities and can be related to ecosystem services. However, trait retrieval is only as reliable as the underlying assumptions about radiative transfer, canopy composition, and sampling representativeness. Furthermore, many management-relevant outcomes—such as habitat quality, restoration success, or degradation risk—are composite constructs that require integrating multiple spectral indicators with contextual information from other sensors, field data, and process understanding.

For these reasons, hyperspectral remote sensing should be viewed as a component of an integrated inference system rather than as a standalone solution [31]. Its unique contribution is the spectral information needed to estimate biochemical and physiological variables, but the translation to sustainability outcomes depends on modeling choices, fusion with complementary observations, and explicit handling of uncertainty. The next section builds on these fundamentals by examining the sensor-to-product pipeline that operationalizes imaging spectroscopy for ecosystem and natural resource management, including platform considerations, preprocessing pathways, retrieval models, fusion strategies, and the emerging emphasis on trustworthy, decision-ready products.

2.7. Literature Search and Synthesis Approach

This review summarizes the current developments in the field of hyperspectral remote sensing in the context of ecosystem management and natural resource management. The search of literature was conducted with the help of organized searches in the large scientific databases, which are Web of Science, Scopus, and Google Scholar, and the keywords were contained in such combinations as: hyperspectral remote sensing, imaging spectroscopy, ecosystem monitoring, vegetation traits, water quality, soil properties, data fusion, and uncertainty quantification. This search focused on the recent publications over the last 15 years and still incorporated the pioneering studies that defined the fundamental aspects of imaging spectroscopy. Relevance of articles was filtered against three criteria:

(1) Methodology for hyperspectral data processing/modeling;
(2) Use in the monitoring of ecosystems, in the management of natural resources, or in decision-making situations related to sustainability;

(3) Validation, uncertainty, or operational deployment deliberations. Literature that dealt solely with laboratory spectroscopy or limited classification issues not related to ecology was only excluded unless they proposed methodological advances that could be used in environmental monitoring.

The synthesis took the form of a sensor-to-decision pipeline framework, instead of urging meta-analysis of individual case studies, which greatly assisted in connecting measurement physics, data processing, modeling strategies, and application to decisions. Such a framework enables methodological innovations to be interpreted in the light of their consequences to the monitoring of operational sustainability, instead of a set of individual technical innovations [16,32,33].

3. Sensor-to-Product Pipeline: Platforms, Preprocessing, and Modeling

Hyperspectral remote sensing becomes actionable for ecosystem and natural resource management only when the full chain from measurement to mapped indicators is treated as an integrated system [34]. The "sensor-to-product" pipeline links platform capabilities and acquisition geometry to calibration, atmospheric and geometric corrections, feature representation, retrieval modeling, fusion with complementary observations, and the production of uncertainty-aware outputs that can be interpreted by end users. Each stage influences the next, and small biases introduced early in the pipeline can propagate into large downstream errors or misleading trends. This section synthesizes recent progress in platforms, analysis-ready processing, modeling strategies, and data fusion, emphasizing how these developments collectively improve robustness, scalability, and interpretability for sustainability applications.

3.1. Platform Landscape and Observation Strategies

The modern ecosystem of the hyperspectral platform covers the field spectrometer space, including proximal imaging spectrometers, UAV-mounted sensors, airborne imaging spectrometers, and in-space missions [35]. Each of the platforms has a different niche based on the tradeoffs in terms of spatial resolution, spectral fidelity, revisit frequency, swath width, signal-to-noise ratio, and flexibility in which it can be used in the acquisition. Field and proximal spectroscopy provide measurements that are highly controlled, facilitate the understanding of processes, spectral library development, and calibration/validation, but have limited spatial coverage. UAV hyperspectral imaging can be used to flexibly map large fields at ultra-high resolution, restore plots, and monitor disturbances more precisely, but the capabilities of UAVs are limited by the variation of the illumination, stability of the flight, and regulatory limits, and UAVs may be difficult to scale to greater extents. Airborne campaigns provide a bridge between plot and landscape scales, typically delivering high signal-to-noise data with well-characterized calibration, making them ideal for trait mapping, biodiversity studies, and method development across heterogeneous regions. Spaceborne hyperspectral observations, while often coarser in spatial resolution, offer the scalability and continuity needed for regional-to-global sustainability monitoring and consistent long-term assessment, especially when paired with systematic processing and harmonization efforts. **Table 1** provides a consolidated overview of hyperspectral platform classes and their typical strengths, constraints, and sustainability use cases, reflecting well-established platform tradeoffs described in the imaging spectroscopy literature. The platform trade-space that conditions achievable spatial detail, revisit, coverage, and signal-to-noise is synthesized in **Figure 3**, highlighting why platform choice strongly governs which sustainability questions are feasible at operational scales [36,37].

Observation strategy is not only a matter of platform selection but also of acquisition timing and geometry. For ecosystem applications, seasonal context can dominate spectral variability, so acquisition windows are often chosen to align with phenological stages that maximize separability of traits or stress signals. In water quality monitoring, acquisition timing relative to bloom dynamics, river discharge events, and sun glint conditions can determine whether retrievals are feasible. Across platforms, geometry matters because BRDF effects and topographic shading can introduce spectral differences unrelated to surface condition. Consequently, planning that accounts for solar elevation, viewing angles, and terrain, and that seeks consistency across repeated acquisitions, can improve comparability and reduce the burden on downstream correction and modeling [38].

Table 1. Hyperspectral Platforms and Suitability for Sustainability Decisions.

Platform Class	Typical Spatial Scale	Typical Temporal Coverage	Strengths for Ecosystem/Resource Management	Limitations	Best-Fit Sustainability Use Cases
Field/proximal spectroscopy	Leaf to plot	Campaign-based (as needed)	High spectral fidelity; controlled geometry; supports spectral libraries and calibration/validation	Limited spatial coverage; scale mismatch to image pixels	Trait mechanism studies; library building; validation for vegetation/soil/water products
UAV hyperspectral	Sub-meter to meters	Flexible, high repeatability locally	Very high spatial detail; supports within-field/patch decisions; rapid post-event mapping	Illumination variability; flight stability; limited area; regulatory/logistical constraints	Precision agriculture; restoration plots; invasive patches; post-fire or storm site assessments
Airborne hyperspectral	Meters to tens of meters	Campaign-based (regional snapshots)	High SNR; flexible acquisition windows; strong for heterogeneous landscapes	Cost and planning; limited temporal continuity	Regional biodiversity/trait mapping; watershed and coastal monitoring; method transfer to satellites
Spaceborne hyperspectral	Tens of meters to coarser (often)	Systematic revisit (mission-dependent)	Regional-to-global consistency; long-term monitoring potential; scalable policy reporting	Mixed pixels; clouds; stricter SNR/coverage tradeoffs; reliance on standardized processing	National/regional sustainability indicators; broad habitat condition; large waterbody monitoring; MRV-style reporting

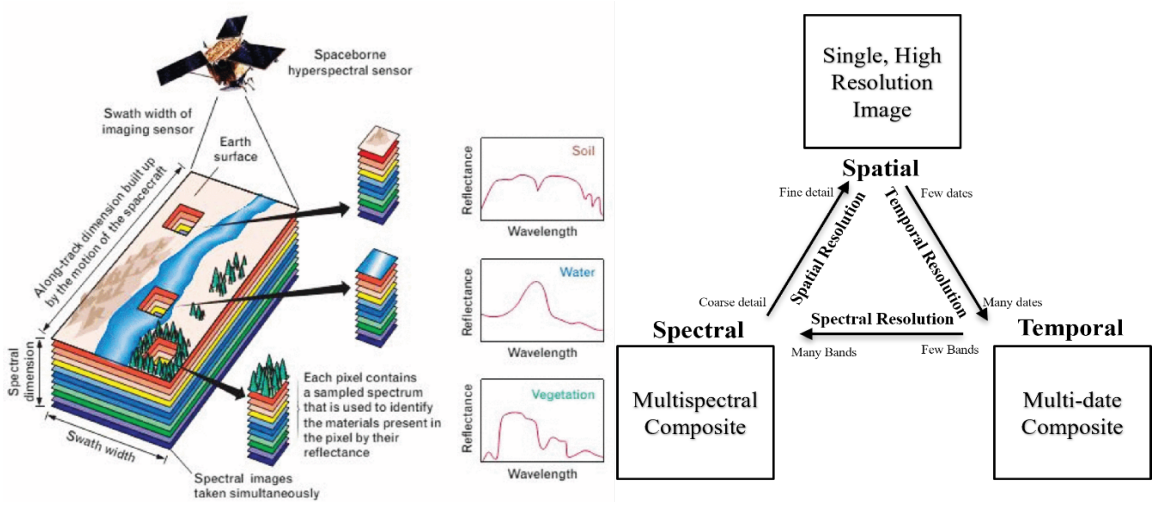

Figure 3. Platform and Scale Trade-Space for Hyperspectral Remote Sensing.

Note: Illustration of the trade-space among hyperspectral platforms, comparing field/proximal, UAV, airborne, and spaceborne systems in terms of spatial resolution, temporal revisit, coverage, and signal-to-noise ratio. Representative sustainability applications are indicated for each platform class [36,37].

3.2. Radiometric Calibration, Stability, and Cross-Sensor Interoperability

Credible products of sustainability require radiometric consistency through time, space, and sensors [4]. Radiometric calibration determines the interrelationship between measured digital numbers and at-sensor radiance; spectral calibration is used to ensure that band centers and bandwidths are known well. In the case of hyperspectral instruments, narrow absorption features may be distorted by small spectral shifts and thus compare the sensors (or measurements on different acquisition dates). Contemporary calibration processes are becoming more and more concerned with coefficient stability, frequent monitoring of drift, and vicarious calibration methods which exploit well-understood target calibration bodies. The steps are notably useful to long-term monitoring and trend detection, where the apparent changes in reflectance are to be reliably ascribed to changes in the ecosystem but not to the conduct of instruments.

Interoperability in cross-sensors is now an important direction as the community shifts towards the multi-platform analysis and is trying to extrapolate airborne insights to satellite products. Harmonization is problematic due to the spectral response functions, SNR, spatial resolution, and stray

lights of various instruments. The retrieval of surface reflectances can also cause systematic biases in indices, absorption measures, and model inputs, even in the case of surface reflectance retrieval. Explicit spectral resampling is therefore a critical requirement of interoperability, as well as prudent treatment of sensor-specific artifacts, and model design has to be either sensor-dependent but bandpass invariant or requires sensor metadata. To be able to monitor operational sustainability, the objective is not full equivalence between sensors but the predictable and measurable differences, which can be adjusted or included in uncertainty estimates [39].

3.3. From Radiance to Surface Reflectance: Atmospheric and Adjacency Correction

Atmospheric correction is a defining stage for hyperspectral processing because it determines whether subtle absorption features reflect surface properties or residual atmospheric artifacts. The challenge is wavelength-dependent: aerosol scattering strongly influences the blue and visible region, while water vapor absorption dominates specific intervals in the shortwave infrared. Advanced atmospheric correction approaches combine radiative transfer modeling with ancillary information on aerosols and water vapor, and they often include explicit treatment of adjacency effects in heterogeneous landscapes. For terrestrial scenes, the objective is typically to retrieve consistent surface reflectance suitable for trait mapping and land condition assessment. For aquatic applications, the objective is frequently to isolate water-leaving reflectance, a much smaller signal that requires careful correction, stringent quality screening, and often specialized algorithms tailored to optically complex waters [6,40].

Adjacency correction and the handling of stray light are particularly important near sharp boundaries, such as shorelines, urban–vegetation edges, or heterogeneous mosaics of bright and dark targets. Without accounting for these effects, reflectance over dark water or dense forest can be biased high, and derived products such as chlorophyll concentration or pigment indices can become unstable. Because adjacency and atmospheric effects vary with wavelength, they can also imprint artificial spectral features that resemble biochemical absorptions. For sustainability applications that depend on early warning signals or subtle trait shifts, robust atmospheric and adjacency correction is often the difference between actionable products and false alarms [41].

3.4. Geometric Processing and Co-Registration for Multitemporal and Multisensor Analysis

Some of the conditions of reliable change detection, model training over datasets, and fusion with complementary sensors include geometric accuracy [42]. Misregistration is especially a problem with hyperspectral imagery due to the possibility of adjacent pixels having different materials and narrowband features that differ greatly even over short distances in heterogeneous ecosystems. To create data cubes analysis-ready, it is necessary to carry out accurate orthorectification, terrain correction, and band-to-band co-registration. Even small spatial displacements can generate spurious trends in time series applications of a small riparian corridor, field boundary, or patchy habitat.

The fact that co-registration is as stringent increases the heightened requirement to co-register in data fusion processes where hyperspectral images are fused with LiDAR, SAR, or thermal images [43]. Fusion can only make sense when the various data sets are superimposed on a common grid with clearly defined uncertainty. In the current workflow, automated tile point matching, digital elevation models of high quality, and sensor-specific geometric models are increasingly employed in the context of enhancing alignment. In the operational monitoring, geometric QA/QC measures and geospatial uncertainty layers are being considered as part of the product delivery, rather than internal processing by analysts.

3.5. Noise Mitigation and Sensor Artifact Correction

Hyperspectral data commonly contain artifacts such as striping, smile effects (spatial variation in band center), keystone distortions (spectral-spatial misalignment), and localized detector anomalies [44]. These issues can imprint structured patterns into reflectance and can bias downstream retrieval models, particularly those that exploit subtle spectral features. Noise characteristics often vary across wavelengths, with lower SNR in the blue and around atmospheric absorption regions. Modern preprocessing pipelines therefore incorporate bad band identification, restriping, deglitching, smile

correction, and spectral smoothing, while attempting to avoid over-smoothing that can erase meaningful absorptions.

A critical point for sustainability applications is that artifact correction is not purely aesthetic [45]. Striping or smile residuals can manifest as spatially coherent "hotspots" that could be mistaken for stress, contamination, or degradation. Conversely, aggressive denoising can reduce sensitivity to early-stage physiological changes. As the field moves toward operational use, there is growing emphasis on transparent reporting of preprocessing choices, the propagation of noise estimates into uncertainty metrics, and community standards for identifying and flagging unreliable spectral regions.

3.6. Feature Representation and Dimensionality Management

The strength of hyperspectral imagery is also its high dimensionality, as well as a modeling challenge [46]. Raw spectra are very rich in information, but also have redundancy, noise, and correlation between neighboring bands. The purpose of feature representation strategies is to maintain diagnostic information and enhance stability, interpretability, and computational efficiency. Classical methods involve continuum removal that separates spectrophotometric features that are being analyzed, derivative spectroscopy that focuses on spectral shape variations, and construction of narrowband indices that feature biochemical or structural attributes. There are dimensionality reduction techniques, which include principal components analysis (PCA) and minimum noise fraction (MNF) transforms, which compress the data but suppress noise, and reduce interpretability when the transformed components are not associated with observable properties.

Recent research is putting more emphasis on representation learning, in which embeddings are trained directly on data to maximize predictive error or transfer. These methods comprise autoencoders, contrastive learning, and transformer-based spectral encoders, which are capable of learning invariant representations to illumination and sensor variations. To monitor the operational sustainability, the choice of representation should be a balance between accuracy and transparency. Learned embeddings may have a positive effect on the performance; however, the decision contexts may need interpretable correlations among wavelengths/ecological processes, which is why a hybrid methodology is a promising solution to combine physically meaningful features with learned representations [47,48].

3.7. Retrieval Modeling: Empirical, Physics-Based, and Hybrid Approaches

Retrieval models are models that change spectra to quantitative approximations of ecosystem variables, including pigments, canopy water content, proxy leaf mass per area, soil organic matter indicators, or water quality constituents [49]. The empirical and statistical techniques of learning, such as partial least squares regression, support vector regression, random forests, and gradient-boosted trees, are still popular as they are able to learn nonlinear relationships and can work well when training data is representative. These models may, however, be prone to domain shift and may be based on correlations that are not universally found between regions or seasons; they are not useful in the general sustainability products on a broad scale unless properly validated and adapted.

Radiative transfer models, which are physics-based models, have been used to relate biochemical and structural parameters to observed spectra. Coupled leaf-canopy models have been shown to provide a mechanistic framework of trait retrieval in vegetation and to extrapolate out of the training domain when parameterization is done appropriately. Bio-optical models in the water environment provide the basis of connection between water constituents and the water optical properties of absorption and scattering, which provide an entry to interpretability and transferability. The drawback of physics-based inversion is that it is frequently ill-posed, and different sets of parameters can give similar spectra, and it can be computationally expensive when dealing with large data sets. These threats have led to the rise in the application of hybrid techniques that involve physical constraints and data-driven learning [50].

Physics-informed neural networks, emulators based on physically realistic radiative transfer models, and constrained learning methods all constitute hybrid physical and ML methods, where interpreted variables must stay plausible. The approaches can enhance generalization by incorporating physical structure in learning, decreasing overfitting to site-specific relations, and offering results that are more in line with ecological knowledge. The practicality of the application in terms of sustainability is that hybrid models can be

used to maintain more stable products in different environments, especially in situations where training data are scarce or unevenly distributed [48].

3.8. Spectral Mixture Analysis and Unmixing in Heterogeneous Landscapes

The ubiquitous nature of mixed pixels, particularly on a satellite scale, has rendered spectral mixture analysis at the center of ecosystem applications [51]. Linear unmixing is a method that perceives the observed spectrum as a weighted average of endmember spectra of pure materials: green vegetation, non-photosynthetic vegetation, soil, and water. Different extensions may be made, like multiple endmember spectral mixture analysis (MESMA), which enables the endmembers to be variable to more effectively describe ecological variability in soils and vegetation types. More complicated cases where linear assumptions are broken by either intimate mixing or multiple scattering are dealt with by sparse unmixing and nonlinear mixture models.

Unmixing is particularly valuable when management objectives involve fractions rather than classes, such as estimating vegetation cover components, mapping invasive species presence within mixed communities, or quantifying habitat composition in fragmented landscapes. It also provides a bridge between ecological theory and remote sensing, because fractional cover can be linked to productivity, erosion risk, or habitat quality. However, unmixing quality depends strongly on endmember selection, library representativeness, and the treatment of illumination and shadow fractions. For operational use, unmixing outputs benefit from explicit uncertainty estimates and from integration with structural measurements from LiDAR or radar to reduce ambiguity [52,53].

3.9. Deep Learning and Scalable Inference

Deep learning has accelerated hyperspectral analysis by enabling joint spectral–spatial modeling and by learning complex representations directly from data. Convolutional neural networks have been widely used for classification and regression on hyperspectral cubes, while transformer architectures increasingly appear in both spectral encoding and spectral–spatial attention frameworks. In ecosystem applications, deep models can capture contextual cues such as canopy texture, patch structure, and spatial patterns that help disambiguate spectral mixtures and improve robustness to noise. They can also support multi-task learning, where related variables, such as multiple traits or land condition indicators, are predicted simultaneously [54,55].

The key barrier to deploying deep learning for sustainability products is generalization [56]. Models trained on a limited set of ecosystems, seasons, or sensors can fail when applied elsewhere. This has driven rapid growth in domain adaptation, transfer learning, and self-supervised pretraining, where models learn from large volumes of unlabeled hyperspectral data and are later fine-tuned for specific tasks with limited ground truth. While these approaches are promising, operational readiness depends on systematic benchmarking, transparent reporting of training domains, and the development of diagnostics for out-of-distribution detection so that users can recognize when predictions are unreliable.

3.10. Data Fusion to Strengthen Robustness and Decision Relevance

Hyperspectral imagery provides chemically and physiologically rich information, but many management questions also require structural, moisture, and energy balance information. Data fusion addresses this need by combining hyperspectral observations with other remote sensing modalities. Fusion with LiDAR can integrate canopy height, vertical structure, and biomass proxies with trait information, improving species discrimination, habitat mapping, and carbon-related assessments. Fusion with SAR can add sensitivity to moisture and structure under cloudy conditions, supporting monitoring in humid tropics and during storm seasons. Fusion with thermal imagery can provide stress-relevant temperature signals and evapotranspiration proxies that complement hyperspectral trait indicators, strengthening early warning frameworks [57].

Another important direction that is critical is the space willing to observe in hyperspectral, which is the spatiotemporal fusion that can be limited by revisit [58]. As hyperspectral snapshots are observed with additional higher frequency multispectral or radar measurements, it is hoped that one can interpolate the trait dynamics or find speedy events without loss of spectral fidelity. These techniques have to be wary of scale mismatch and error propagation, or fusion may give overconfident products or cause artifacts that destroy trust.

Consequently, the current fusion pipes pay more attention to creating uncertainty-aware fusion, direct co-registration quality measurements, and validation strategies that assess the accuracy, as well as stability over time and conditions.

3.11. Uncertainty Quantification, Interpretability, and Product QA/QC

To make sustainability-based decisions, hyperspectral products must be credible based on the clarity of uncertainty characterization and interpretability. Uncertainty has various sources, and these include calibration drift, atmospheric correction residual, geometric microtitration, noise and artifact, mixed pixel, and model extrapolation out of training conditions [59]. The quantification of uncertainty is thus not an operation but an architecture that ought to be fully incorporated through the pipeline. Naive frameworks, Ensemble learning, Bayesian Approaches, and Bayesian conformal prediction have been proposed as a practical solution to generate uncertainty at scale, and error propagation models can be used to bridge the gap between preprocessing and retrieval uncertainty in the absence of intermediate diagnostics.

Interpretability is a complement of uncertainty that is used to explain why a model provides a particular result. Interpretability in hyperspectral applications can be based on wavelength attribution studies that determine what spectral regions are used to make predictions and whether they are related to known absorption features. Physical plausibility tests, like verification that the variables retrieved are within realistic bounds, and the response to changes in phenology and illumination is realistic, are becoming part of QA/QC. In the case of operational products, the joint assurance of predictions, uncertainty layers, quality flags, and recording of processing assumptions gives a basis upon which the user has faith in it and the responsible incorporation into the management workflows [13,60].

3.12. Toward Analysis-Ready Hyperspectral Data and Scalable Product Generation

A defining trend in hyperspectral remote sensing is the movement toward analysis-ready data and standardized processing pipelines that lower barriers for broad adoption [61]. Analysis-ready approaches aim to deliver data cubes that are already corrected for geometry and atmosphere, include documented spectral response functions, provide quality masks for clouds, shadows, and noisy bands, and expose metadata needed for harmonization and fusion. Cloud-native data infrastructures and scalable computing frameworks are increasingly used to process large hyperspectral volumes, enabling regional and global products that would be impractical with traditional desktop workflows. Because downstream ecological inference is highly sensitive to upstream calibration, atmospheric correction, and co-registration, we summarize the sensor-to-product workflow and major uncertainty entry points in **Figure 4**.

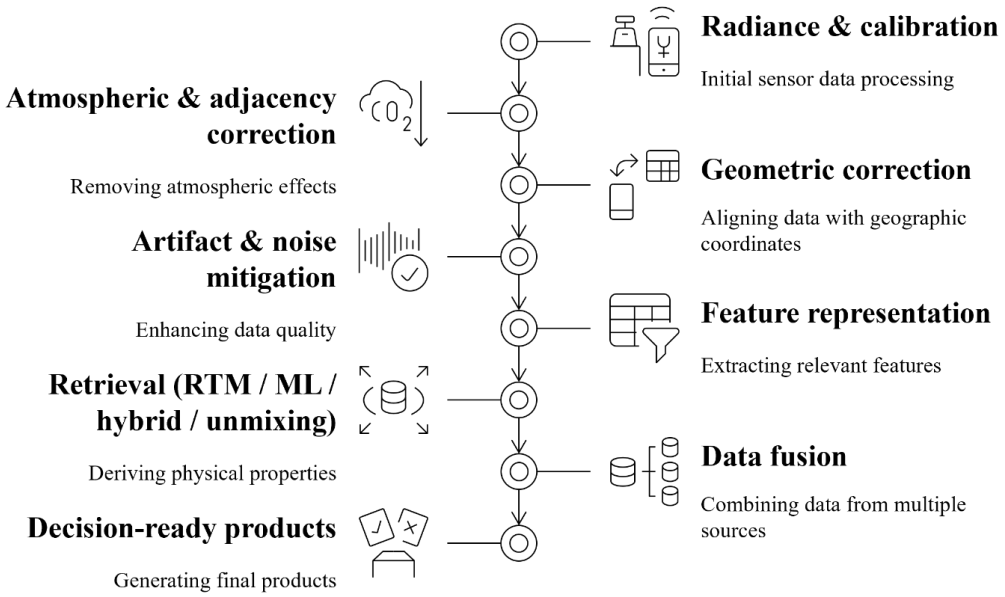

Figure 4. End-to-End Sensor-to-Product Pipeline with Uncertainty Propagation.

The practical significance for sustainability is that standardization enables comparability and reproducibility, which are essential for long-term monitoring, policy reporting, and cross-jurisdictional resource management. At the same time, standardization must accommodate ecological diversity and sensor differences, suggesting that future operational pipelines will likely combine shared core preprocessing with configurable, application-specific modules and explicit uncertainty reporting. Building on these pipeline advances, the next section examines how hyperspectral remote sensing is being translated into decision-centered applications and operational pathways across biodiversity, vegetation function, disturbance monitoring, agriculture, water quality, soils, and resource impact assessment. **Table 2** summarizes the major stages of the hyperspectral sensor-to-product pipeline, common failure modes, and recommended QA/QC outputs that support robust inference and reproducible sustainability products [62].

Table 2. Sensor-to-Product Pipeline: Recommended Processing and Modeling Options.

Pipeline Stage	Core Objective	Common Approaches (Representative)	Typical Failure Modes	Recommended QA/QC Outputs
Radiometric & spectral calibration	Stable, comparable radiance and band positions	Laboratory calibration; vicarious calibration; spectral response characterization	Drift; band shifts; cross-sensor offsets	Calibration logs; sensor stability metrics; bandpass metadata
Atmospheric & adjacency correction	Retrieve surface/water-leaving reflectance	RT-based correction; aerosol/water vapor retrieval; adjacency correction near edges	Residual absorption artifacts; shoreline contamination; glint impacts	Per-pixel quality masks; water vapor/aerosol indicators; "bad band" flags
Geometric correction & co-registration	Pixel-level alignment across time/sensors	Orthorectification with DEM; tie-point matching; band-to-band registration	Spurious change signals; fusion mismatch	Registration error maps; co-registration scores; edge-mismatch diagnostics
Artifact & noise mitigation	Remove instrument-induced patterns	Destriping; smile/keystone correction; deglitching; controlled smoothing	"False hotspots"; over-smoothing of absorption features	Striping indices; noise estimates by wavelength; flagged spectral intervals
Feature representation	Stabilize inputs; preserve diagnostic information	Continuum removal; derivatives; band selection; PCA/MNF; learned embeddings	Loss of interpretability; sensitivity to noise	Feature provenance; wavelength importance diagnostics; sensitivity tests
Retrieval/inference	Convert spectra to variables/indicators	Empirical ML; RT inversion; hybrid physics–ML; unmixing	Domain shift; ill-posed inversion; endmember mismatch	Cross-domain validation; plausibility constraints; residual/error maps
Data fusion	Reduce ambiguity; add structure/moisture/thermal context	HS + LiDAR; HS + SAR; HS + thermal; spatiotemporal fusion	Error propagation; misalignment; inconsistent resolutions	Fusion uncertainty layers; alignment QA; modality contribution diagnostics
Uncertainty & interpretability	Decision-grade trust	Ensembles; Bayesian approximations; conformal methods; OOD detection	Overconfidence; misleading explanations	Confidence maps; OOD flags; model cards (training domain, limits)

4. Decision-Centered Applications and Operational Pathways

Hyperspectral remote sensing becomes most valuable for sustainability when it is framed not as an end in itself, but as a means to answer specific management questions with defensible evidence [16,63]. In the ecosystem and natural resources sectors, managers are generally required to be aware of where sensitive resources are situated, their state, the forces that are causing the change, and the effects of interventions on the paths. Imaging spectroscopy can help in overcoming the visibility or indistinctness of biochemical and material properties in the broadband imagery, allowing diagnostic and proactive transitions to occur in imaging. But the path between spectral measurement and management action is conditioned by the presence of practical requirements, such as spatial and temporal compatibility with decisions, validation, reflective of operational conditions, and designs of products that convey uncertainty and decision criteria. This section reviews major application areas and emphasizes how hyperspectral observables translate into decision-ready products and services. **Table 3** links representative management questions to hyperspectral observables, product outputs, and minimum validation requirements across major sustain-

ability application domains.

4.1. Biodiversity, Habitat Quality, and Functional Trait Diversity

Field inventories and coarse remote sensing proxies, such as land cover class, structural heterogeneity, or greenness indices, have long been used in the biodiversity monitoring field. Hyperspectral records provide an additional dimension by recording spectral dissimilarity linked to plant pigments, water content, and biochemical mix, which can usually have a systematic change across plant species, functional types, and conditions of the habitat. Imaging spectroscopy may be used to assist in the mapping of different species or assemblages in vegetation-dominated ecosystems when phenological timing is well chosen and spectral separability is high enough. Hyperspectral data can be especially useful in estimating functional traits and trait diversity, even in cases where species-level classification is difficult, which makes it possible to characterize the so-called functional composition that relates more directly to ecosystem processes than taxonomy does [64].

Table 3. Decision-Centered Applications: Management Question to Hyperspectral Observable to Decision-Ready Product.

Application Domain	Typical Management Question	Key Hyperspectral Observables	Example Product Outputs	Validation Needs (Minimum)
Biodiversity & habitat	Where are priority habitats and how is condition changing?	Trait/functional composition; pigment and water-related features; subpixel fractions	Habitat condition index; functional diversity layers; change hotspots	Plot inventories; trait sampling; cross-season repeat measurements
Vegetation function & restoration	Is recovery real, sustained, and on track?	Chlorophyll-related metrics; canopy water; dry matter traits; material fractions	Restoration performance maps; recovery trajectory classes	Time series plots; survival/cover metrics; reference/control sites
Stress & disturbance early warning	Where is stress emerging before visible decline?	Subtle pigment shifts; water absorption changes; anomaly signatures vs. seasonal baseline	Stress anomaly alerts; risk prioritization zones	Phenology context; independent stress indicators; false-alarm analysis
Sustainable agriculture	Where should inputs be reduced or targeted?	Nutrient/water stress proxies; within-field spectral heterogeneity	Variable-rate management zones; disease scouting layers	Field sampling; yield/quality data; agronomy records
Water quality (inland/coastal)	Where are blooms/turbidity risks and how are they evolving?	Chlorophyll-a features; CDOM slopes; scattering/turbidity signals	HAB risk maps; turbidity plumes; compliance summaries	Coincident in situ sampling; glint/adjacency screening; concentration-range coverage
Soils & land degradation	Where are SOC/salinity/degradation risks highest?	Soil absorption features; organic matter darkening; moisture/salinity indicators	Degradation susceptibility; restoration priority; salinity risk	Soil lab samples; moisture controls; stratified sampling across soil types
Extraction impacts & compliance	Are disturbances and reclamation outcomes consistent with commitments?	Exposed materials; stressed vegetation; downstream optical changes	Disturbance footprint; reclamation verification; screening for field audits	Site inspections; structural/context data; documented uncertainty for auditability

The management aspect associated with the use of the trait-based hyperspectral products is that they can be used to inform the assessment of habitat quality in terms of a change in the plant functional strategies in relation to disturbance, degradation, or restoration. As an example, the pigment-related traits can display spatial patterns that indicate stress, which can be used in sensitive habitats, whereas shortwave infrared biomarkers of water and dry matter may indicate the differentiation of functional states associated with resilience. The problem related to operations is that biodiversity and habitat quality are complex constructions, and the trait maps are usually contextually interpreted. The most justifiable strategies, therefore, combine hyperspectral trait recovery with structural data, landscape setting, and field-based ecological indicators, which generate composite habitat condition items that are clear concerning their contributing variables and uncertainty [65].

4.2. Vegetation Function, Carbon Dynamics, and Restoration Monitoring

The main focus of sustainability programs, such as conservation finance, carbon markets, and national reporting, is on monitoring of ecosystem functioning and carbon-

related dynamics. Imaging spectroscopy has a role to play as it estimates canopy biochemical and physiologic variables which mediate productivity and stress reactions, including chlorophyll-related measures, canopy water content, and dry matter proxies. Although hyperspectral data do not directly trace carbon stocks, as the structural sensors can assist in biomass estimation, the information provides very useful data on carbon fluxes and vegetation condition, such as photosynthetic potential indicators and susceptibility to droughts [66].

The capacity to measure vegetation condition and functional restoration is frequently a more significant requirement in restoration settings than presence/absence mapping. The changes in the trait of maturation, improved water status, and altered species or functional composition can be used to differentiate between superficial greening and actual recovery with the aid of hyperspectral products [67]. This is especially useful in the reclamation of post-mining, the restoration of riparian, reforestation, and grassland restoration, where results have to be measured over time. Time-series designs can be used to operationalize restoration monitoring because they accommodate phenological and climate variability, whereas validation strategies seek to explicitly test whether hyperspectral indicators are monitoring independent measures of function, i.e., field-based trait measurements, survival rates, or ecosystem performance indices. These applications are becoming mature, and full adoption must be achieved based on standardized protocols in repeated surveys, harmonizing the preprocessing and clear reporting of uncertainty to ensure that the claims of restoration success can be defensible by audit.

4.3. Early Warning of Stress, Disturbance, and Recovery Trajectories

A major promise of hyperspectral remote sensing is early detection: identifying stress signals before they become visible in canopy browning or structural decline. Physiological stress often alters pigment composition, water status, and cellular structure in ways that produce subtle but detectable spectral changes, especially when narrowband features are resolved and when confounding variability is controlled. In practice, stress detection is rarely a single-variable problem. Drought, heat, nutrient deficiency, pests, and disease can produce partially overlapping spectral responses, and many ecosystems exhibit great seasonal changes that can overwhelm stress signals [68,69].

Operationally defined early warning is thus most likely to be most accurate when presented as an anomaly detection as compared to an anticipated seasonal path, as opposed to as a one-day designation. Even with sparse multi-temporal hyperspectral observations, the application of complementary sensors and process knowledge may be used to decouple phenological patterns with abnormal departures. In the context of wildfire-related management, imaging spectroscopy can be used to obtain such information that is related to canopy moisture and fuel properties, influencing the risk evaluation in the presence of favorable conditions, and is beneficial to supplement thermal and meteorological indicators. Hyperspectral time series can record succession and re-establishment of function by monitoring recovery trends after disturbance by recording changes in traits and materials recorded in hyperspectral time series. The most significant operational impediment is the strength: early warning products should reduce false alarms and present the information with confidence to enable making risk-based decisions, e.g., prioritizing field checks, devoting scarce treatment resources, or conducting specific warnings [70].

4.4. Agriculture and Sustainable Intensification across the Field-to-Watershed Nexus

Sustainable farming involves controlling the inputs and outputs and minimizing the externalities that include the loss of nutrients, depletion of water, and soil erosion. Hyperspectral sensing would be highly applicable to precise management since it is able to identify variations in biochemicals and physiological changes in regions, which are linked to nutrient status, water stress levels, and disease-related effects, usually before yield decrease can be observed. In the high-resolution UAV and airborne contexts, hyperspectral imagery can aid in the administration of variable rates by mapping the within-field variability in crop health and also in the detection of hotspots, which should be targeted to assist [71].

On a larger scale, hyperspectral products can be useful in terms of sustainability in the sense that they can monitor crop conditions and stress in crop regions uniformly, provide early alerts on the effects of drought, and enhance the characterization of crop quality characteristics that may be linked

with management practices [72]. But when moving to a field experiment to an operational, regional scale, scaling presents issues to do with mixed pixels, phenological variation across crop bars, and inter-variety inter-management regime transfer. Hyperspectral information mostly works best when used in conjunction with other sources of information, such as thermal measurements to detect evapotranspiration proxies, radar to understand the structure and sensitivity of canopies, and agronomic models to give information on which spectral signals should be interpreted. Validation should also change towards measures of accuracy on a plot level to decision-relevant measures, such as whether hyperspectral guidance uses less input, is it more efficient in using water, or does it reduce the risk of nutrient runoff without reducing production.

4.5. Inland and Coastal Water Quality and Aquatic Ecosystem Health

The most direct sustainability uses of imaging spectroscopy are in water quality since some constituents of practical interest have characteristic optical signals within the visible spectrum [73]. Hyperspectral sensors can enhance the resolution between chlorophyll a, CDOM, and suspended sediments more than multispectral systems, so that the dynamics of eutrophication, the plumes of sediments, and the contributions of organic matter can be more accurately mapped. It assists in the management of drinking water reservoirs and harmful algal blooms in freshwater systems and in coastal environments. It helps to track runoff effects, habitat loss, and changes in water clarity pertaining to seagrass and coral reefs.

Atmospheric correction, glint, adjacency effects along the shoreline, and optical complexity of inland waters should be closely considered in terms of operations deployment. Since water-leaving reflectance may constitute a small percentage of the overall signal at the sensor, preprocessing errors may have a profound effect on the derived products. Ready-to-use aquatic products are thus advantaged by transparent quality screening and uncertainty reporting, and validation programs that match remote sensing measurements with in situ measurements acquired across representative concentration scales. Under these circumstances, hyperspectral water quality mapping has the potential to support spatially focused management responses, including determining bloom-prone areas, effective monitoring networks, and determining the success of watershed nutrient reduction plans [74,75].

4.6. Soils, Rangelands, and Land Degradation Monitoring

Land degradation is a process that entails the interaction processes of loss of soil organic matter, soil erosion, salinization, shrub vegetation, and changes in hydrology, which have a tendency to be reflected in both vegetation and soil spectral properties. Hyperspectral sensing plays a role in solving diagnostic characteristics of the soil mineralogy, organic matter, and moisture, as well as offering better characterization of the sparse vegetation state in drylands and rangelands, where the soil background has a great effect on the reflectance. Imaging spectroscopy could be used in rangeland management to complement the monitoring of forage condition, invasive spread, and the gradients of degradation, especially when used together with structural information and ecological context [76,77].

Operational land degradation assessment benefits from approaches that explicitly handle heterogeneity and mixed pixels, because many degraded landscapes are mosaics of bare soil, litter, shrubs, grasses, and biological crusts. Time series are also critical, as degradation signals must be separated from interannual climate variability. In soil-focused applications, moisture variability can confound retrievals of organic matter or mineral indicators, requiring either simultaneous estimation of moisture effects or acquisition strategies that reduce moisture-driven variability. Decision relevance increases when hyperspectral indicators are linked to thresholds that matter for management, such as erosion susceptibility, salinity risk, or restoration priority, and when products are accompanied by uncertainty information that supports risk-based planning [78].

4.7. Resource Extraction Impacts, Environmental Compliance, and Reclamation Verification

Changes in mineral surfaces, bare tailings, vegetation stress, and downstream water quality changes can result in strong spectral signals with natural resource extraction. Mineral and alteration mapping has long been done by hy-

perspectral remote sensing; in the context of sustainability, the focus has changed to the impact assessment, compliance supervision, and verification of reclamation. Imaging spectroscopy has found use in the identification of materials on tailings or disturbed ground, monitoring vegetation recovery on reclaimed areas, and, along with aquatic techniques, aids in monitoring water bodies that undergo sedimentation or contamination processes that change optical characteristics [79].

The utilization worth of such applications relies on transparency in governance and confirmation since compliance situations demand justifiable affirmations. The products should be stable over time and sensor configurations, and should be clear of limitations. It may be necessary to integrate with other sources of data, including topography and structural change with LiDAR, surface moisture and deformation sensitivity with radar, and regulatory-grade measurements with in situ sampling. A properly designed hyperspectral monitoring can also minimize the necessity of using a few inspections, as it includes spatially-rich screening instruments that can focus on field checks and enable high transparency in reporting the results of the reclamation [80].

4.8. Translating Hyperspectral Science into Decision-Ready Services

More than better algorithms are needed to make this transition between scientific demonstrations and operational services: product definitions that are compatible with decision cycles and institutional constraints are needed [81]. Hyperspectral products that are ready to make a decision have a number of attributes in common: they are provided in forms that are analysis-ready, they have quality and uncertainty layers, and they are described in terms that correspond to management action and that do not rely on remote sensing measures alone. As an example, a map of a biochemical parameter may not be required by the managers; instead, they require a map of risk groups, the priority of intervention, or the state of compliance with intervention, with the information on the confidence and the advice on how to interpret it.

Of particular importance are benchmarking and reproducibility since hyperspectral workflows possess numerous degrees of freedom in both preprocessing and the modeling process, which may cause unnecessary variability of results across studies [82]. Operational pathways enjoy a standardized processing pipeline, model assumptions that are recorded in documentation, and reporting practices that render products auditable. Cloud-native computation and data cube systems are becoming increasingly able to provide scalable processing and allow integration with complementary datasets, though the practical use of these systems remains dependent on the governance challenges of data access, long-term sustenance, and trustworthiness by stakeholders. The end user co-design is consequently an essential aspect of successful deployment: the product requirements, tolerable uncertainty, and action thresholds should be negotiated with agencies and practitioners, and the obtained services should be improved through the process of iteration, based on the usability and actual performance.

To conclude, hyperspectral remote sensing is rapidly evolving with regard to areas of application that are the core of sustainability [4]. Specificity of the biochemical and material contribution is its distinguishing contribution, providing the opportunity to monitor the functionality and detect it early in the case of confounding factors controlled. The next step, which is to convert that specificity into a set of reliable and scalable services, is contingent upon strong pipelines, representative validation, uncertainty communication, and product design that is aligned with the stakeholders. These needs drive the generation of challenges and directions of the future, which are addressed in Section 5, where transferability, ground truth bottlenecks, preprocessing sensitivities, and trustworthy modeling are considered the decisive factors of whether imaging spectroscopy could realize its sustainability potential at scale.

In the case of operational monitoring applications, quantitative benchmarks are becoming more and more demanded to measure the reliability of the models. Retrieval models used in vegetation trait mapping typically show coefficients of determination (R^2) of 0.6 to 0.9 and relative error of 10–25% (depending on trait and complexity of the ecosystem). In good optical conditions, water-quality retrievals of chlorophyll a or suspended sediments can be obtained with an error of 10–30%. In case of management applications, the uncertainty levels should be clearly presented, such as with achieved confidence intervals or with risk levels that are expressed in terms of probability, to ensure that decision-makers can read predictions with loss tolerances [83,84].

4.9. Hyperspectral Remote Sensing in Context: Comparison with Alternative Monitoring Approaches

Hyperspectral remote sensing needs to be viewed as being in an ecosystem of environmental monitoring technologies. Multispectral satellite sensors are still the key to comprehensive monitoring of the land due to the high temporal coverage and extended history. Nevertheless, they have fewer spectral bands, and the diagnostic biochemical features are not easily resolved, so they may need empirical indices, which are sensitive to other confounding factors, e.g., soil background or canopy structure [16].

LiDAR structural remote sensing methodologies are used to give supplementary data on vegetation height, canopy structure, and biomass. Radar sensors have extra sensitivity against moisture and structural characteristics and can continue to observe during cloudy weather. Although these modalities are very useful in monitoring the ecosystem, they do not usually have the spectral selectivity needed to provide a direct indication of biochemical characteristics or water constituents.

Hyperspectral measurements are thus in a unique niche: they are chemical and physiological sensitive, with other modalities offering structural or temporal context. Practically, the strongest sustainability monitoring systems continue to integrate hyperspectral diagnostics with LiDAR, SAR, and multispectral time series in order to achieve diagnostic specificity and spatial coverage and continuity [85,86].

5. Challenges, Gaps, and Future Directions

The high growth rate in the development of hyperspectral remote sensing has made its future as well as its limitations in sustainability-based ecosystem and natural resource management, understandable [87]. Although imaging spectroscopy is capable of extracting information-rich pointers to biochemical composition, physiological state, and material properties, operational deployment still faces challenges, which have been manifested across the different domains: one lacks consistent transferability across space, time, and sensors; there is a bottleneck in ground truth collection and validation; there is always the persistent problem of mixed pixels and scale mismatch; it is always sensitive to atmospheric and angular effects; and there is always the problem of communicating uncertainties reliably in the decision environment. These problems are not technical in nature and need to be looked at. It identifies the feasibility of hyperspectral products to sustain defensible policy reporting, risk-based management, and long-term monitoring in comparison to the changing climate conditions and land-use regimes. This segment is a summary of the most significant issues and research avenues that could be adopted to fast-track the transformations from demonstrations to viable, large-scale sustainability services.

5.1. Generalization across Regions, Seasons, and Sensors

It is generally accepted that the major challenge to scaling hyperspectral ecosystem products is generalization [31]. Most models of retrieval do very well in the ecosystems in which they were designed, but their performance can rapidly diminish when used in other ecosystems, phenological stages, climatic regimes, or sensor configurations. The motives of this change of domain are varied. The ecological modulation of trait-spectra relationships may depend on canopy structure, soil background, species composition, and phenology, which are region- and season-dependent. From an observational perspective, the systematic spectral shifts caused by the differences in viewing geometry, atmospheric state, band pass functions, and noise properties are independent of surface conditions. Even with the successful retrieval of surface reflectance, small errors in specific spectral regions can have inappropriate impacts on models relying on subtle absorption patterns.

Harmonization and model design will probably be the strategies of the future in generalization. Harmonization is concerned with eliminating sensor-induced variability by enhancing calibration, explicit spectral resampling, and applying atmospheric and BRDF [88]. Model design aims at enhancing robustness in terms of feature representations that capture physically expressed absorptions, regularization, and domain adaptation, and in multi-domain training approaches that expose models to increased variability. Most importantly, the evaluation procedures should be changed to include more than random train-test splits within one scene. To be used in sustainability, realistic benchmarks need to focus on cross-site, cross-year, and cross-sensor transfer, where the models are explicitly tested to be robust when the agencies have to

operate in monitoring the state of things.

5.2. Ground Truth Limitations and Validation Realism

Hyperspectral products can only be as reliable as the ground truth data is. Traits, species composition, soil properties, or water constituents that are to be measured in the field are costly and time-intensive, and sampling tends to be skewed to reach convenient locations, pleasant days, and brief campaign periods [89]. These biases cause a difference between the variability represented by training data and the variability that will be experienced in actual deployment. Moreover, the mismatch of the scales is usually present: many ecological measurements are made at the scales of a leaf, plate, or point; the pixels of hyperspectral images are larger and sum up a variety of elements and light conditions. High levels of temporal variability in aquatic systems can make in situ samples non-coincident with overpass times, challenging the validation of dynamism and water quality gradients in a bloom.

To achieve a better validation realism, methodological and infrastructural improvements are needed. In terms of methodology, stratified sampling along environmental gradients, sampling repetition on a seasonal scale, and clear validation of field measurements in correspondence with pixel spatial support of an image are all necessary in validation strategies [90]. The uncertainty of field measurements and geolocation is to be recorded and carried into model analysis instead of being considered insignificant. The community would also be enhanced infrastructurally through maintained networks of observation and common datasets of benchmark data containing standardized field protocols, metadata on sampling conditions, as well as cross-platform hyperspectral data. In cases where the sustainability programs are mandatory, requiring reporting and verification, the creation of open validation standards is as essential as algorithmic innovation, since it is the foundation of confidence, auditability, and cross-jurisdictional comparability.

5.3. Mixed Pixels, Scale Mismatch, and Ecosystem Heterogeneity

Mixed pixels do not represent a niche issue but a fundamental feature of ecosystem measurements, particularly in discontinuous topography and at the satellite resolution. The causes of heterogeneity are patchy vegetation, beneath the canopy and litter cover, soil exposure, microtopography, and shadow portions that vary with the illumination geometry [91]. Mixed spectra may compromise both empirical models, which may implicitly assume homogeneous targets and physics-based models, the parameterizations of which may fail to reproduce subpixel variability. The resulting vagueness is especially important in the context of sustainability that relies on fine-scale aspects, e.g., riparian buffers, small wetlands, invasive species patches, or early-stage degradation hotspots.

The future trends of dealing with heterogeneity will probably concern more integration of unmixing and structural data, as well as object representations. The spectral mixture method is capable of estimating subpixel proportions of important components, although its accuracy requires representative endmember libraries and shadow and illumination care. LiDAR or photogrammetry structural information can be used to constrain canopy structure and can be used to separate biochemical signatures of structural and background variables. The object-based and segmentation workflows can match analysis units to ecologically significant patches instead of pixels to decrease noise and enhance interpretability. Finally, to scale hyperspectral indices to management units, multi-scale representations might have to be adopted, whereby fine-resolution UAV or airborne data is used to interpret and to calibrate coarser satellite products [92,93].

5.4. Preprocessing Sensitivities and Hidden Failure Modes

It is a fact that hyperspectral retrieval accuracy is highly affected by preprocessing steps, which are at times regarded as normal. Spectral distortions that can resemble or obscure ecological information can be caused by atmospheric correction residual, adjacency effects, BRDF and topographic effects, band-to-band misregistration artifact, and sensor artifact. These problems may be invisible, positionally determined, and wavelength-dependent, and are hard to realize without special diagnostics. Preprocessing biases in time series or multi-sensor processes may generate artificial trends that are all too readily confused with ecosystem change, leading to a lack of trust and potentially misguided managerial responses [94].

Blind failure modes have to be minimized not only by better algorithms but also by better transparency Algorithms. The systematic errors can be reduced using algorithmic techniques that support atmospheric correction, including adjacency and adapting to different surface types, and geometric processing techniques can reduce artifacts due to misregistration. Transparency also demands that processing pipelines generate quality flags and diagnostic layers that can allow users to discover locations where reflectance is unreliable, like in high water vapor, glint-contaminated water pixels, shadowed terrain, or aerosol-laden conditions. In the case of the operational sustainability services, the growing significance of treating QA/QC outputs as first-class products that are delivered along with the main indicators, and not processing artifacts, takes place. This strategy justifies responsible use and enables managers to consider the use of confidence in ranking interventions [95,96].

5.5. Trustworthy AI, Uncertainty, and Decision-Grade Interpretability

As machine learning and deep learning become central to hyperspectral inference, the need for trustworthy AI has become more acute [97]. Sustainability applications often involve high stakes: decisions about water advisories, fire risk mitigation, restoration investment, or compliance monitoring can affect livelihoods and ecosystems. In such contexts, accuracy alone is insufficient. Users need to know where and when predictions are reliable, what drives the predictions, and how uncertainty should shape actions. A common failure mode of complex models is overconfidence under domain shift, where predictions appear precise but are systematically wrong because the model is operating outside its training domain.

Future work will likely expand the role of uncertainty quantification and out-of-distribution detection in operational hyperspectral products. Ensemble methods, Bayesian approximations, and conformal approaches can provide calibrated uncertainty estimates, while embedding-based novelty detection and sensor/phenology-aware diagnostics can flag conditions where models are likely to fail. Interpretability should also be strengthened by linking model explanations to known spectral features and physical mechanisms, rather than relying solely on generic saliency visualizations. In addition, model documentation practices—such as clearly stating training domains, preprocessing assumptions, and known limitations—are essential for responsible deployment. For sustainability reporting and governance, these practices provide a foundation for auditability and for building institutional trust in hyperspectral products [98].

5.6. Emerging Approaches: Hybrid Physics–ML, Self-Supervision, and Foundation Models

The way to overcome data constraints and enhance generalization is promising, and one of the approaches is the creation of hybrid strategies that select physical constraints and data-driven learning. Physics-informed models can encode the relationships of radiative transfers and impose plausible behavior, making it less likely than models to learn spurious correlations. Components of radiative transfer and emulators that are differentiable and scale to computationally feasible sizes can use physically grounded reasoning in contemporary training-based learning paradigms through the use of inversion. Bio-optical models coupled with learning-based corrections have the potential to enhance robustness in optically challenging waters in aquatic systems and still be interpretable [99].

Simultaneously, the concepts of self-supervised learning and foundation models are becoming popular in hyperspectral analysis [100]. Since hyperspectral data have large volumes of data without ground truth, self-supervised pretraining has provided an avenue to acquire general spectral representations that can be conditioned on narrow objectives under limited labels. The prospect is to create representations that are sensitive to sensor variations and variations in illumination, and that are sensitive to ecological patterns across biomes. Nevertheless, these models will need to be governed with care when deploying sustainability, such as transparency of training data, systematic testing on a multiplicity of environments, and a way to avoid the convenient use in areas where the model has not yet been tested and validated.

5.7. Operational Roadmaps: Standards, Scalability, and Stakeholder Alignment

This is not merely a question of scientific innovation to transition to operational hyperspectral sustainability services,

but it needs standards, scalable infrastructure, and ongoing interaction with end users [7]. There should be standardization on a variety of levels, such as preprocessing, meaning analysis-ready data, reporting standards of reflectance and derived products, benchmark data to compare across studies, and operational working standards. Scalability is further based on cloud-native processing and data cube systems, which are capable of managing regional and global products without compromising traceability of processing steps and version control of models.

Stakeholder alignment is also important. The decision-makers need products that are aligned with institutional decision cycles, stipulations of the law, and resource binding. Co-design processes can help illuminate what indicators are important, what uncertainty is tolerable, and how results are to be reported; as a continuous variable, risk category, or as a condition to enact field checking. Integrating hyperspectral products into overall decision systems, which include other complementary sensors, field monitoring networks, and process models, is more likely to achieve operational success because this approach allows triangulation and eliminates dependence on any one data stream. Transparency and equity also play a key role in the context of sustainability: the availability of data and procedures, the intelligibility of constraints, and the sound management of monitoring products are other issues that ensure that imaging spectroscopy is a tool of stewardship instead of a tool of injustice [101].

Table 4 consolidates the major barriers to operational hyperspectral sustainability services and summarizes mitigation pathways emphasized across the literature, including harmonization, realistic validation, uncertainty-aware delivery, and stakeholder-aligned product design [102].

Table 4. Challenges and Mitigation Pathways toward Operational Sustainability Services.

Challenge	How It Appears in Practice	Why It Matters for Sustainability	Mitigation Strategies	Priority Research Direction
Domain shift (space/time/sensor)	Models degrade across regions, seasons, sensors	Unreliable trends; limited scalability	Harmonization; multi-domain training; domain adaptation; sensor-aware modeling	Transfer benchmarks; physics-guided generalization
Ground truth scarcity & bias	Few sites, uneven sampling, scale mismatch	Weak validation; low trust in reporting	Stratified sampling; sustained networks; pixel-support alignment	Community reference datasets; standardized protocols
Mixed pixels & heterogeneity	Subpixel mixtures dominate at satellite scale	Misleading retrievals in fragmented habitats	Unmixing + object-based units; fusion with structure; multi-scale designs	Endmember libraries; uncertainty-aware unmixing
Preprocessing sensitivities	Atmosphere/BRDF/topography artifacts mimic signals	False alarms or missed early warnings	Robust correction + QA flags; diagnostic layers; consistency checks	Automated QC; propagation of preprocessing uncertainty
Overconfident AI outputs	High confidence under OOD conditions	Risky decisions; credibility loss	Calibrated uncertainty; OOD detection; model cards	Trustworthy AI for imaging spectroscopy
Operational integration	Products don't match decision cycles/workflows	Low adoption despite technical success	Co-design; risk classes/thresholds; reproducible pipelines	Decision-centered product standards and MRV alignment

Through adversities and the way forward, several priorities stand out as determinant in the achievement of the sustainability potential of hyperspectral remote sensing [87]. To enhance generalization, it is necessary to have both harmonized data and inter-domain robust cross-domain models. The validation should change to representative, multi-site, multi-season standards that should have sustained field networks. The combination of unmixing, structural information, and ecologically relevant spatial units is required for heterogeneity and mixed pixels. The preprocessing needs to be made more open using standardized QA/QC products and uncertainty propagation. Lastly, there are reliable AI practices, including calibrated uncertainty, out-of-distribution detection, and physically grounded interpretability, which should be used in decision-grade products.

These priorities are directed to a future where imaging spectroscopy is no longer viewed as a specialized dataset, but rather as part and parcel of integrated systems of environmental intelligence [103]. Combined with structural and thermal measurements, anchored in sound field validation, and providing standardized, uncertainty-conscious pipelines, hyperspectral remote sensing can help to support early warn-

ing, targeted response, and responsible sustainability reporting at scales sufficient to be commensurable to current issues in the environmental field. This is summarized in the final section as a series of practical lessons on what hyperspectral remote sensing is able to provide currently, what is still in development, and how the discipline can best advance the sustainability limits in ecosystem and natural resource management.

6. Conclusions

Hyperspectral remote sensing is no longer a niche analytical service but a fast-developing support of the sustainability-focused ecosystem and natural resource management. Imaging spectroscopy offers direct sensitivity to biochemical and material properties, which form the basis of ecosystem operation, degradation pathways, and recovery mechanisms through the resolution of continuous, narrow-band spectral information. In both aerial and water resources, this supplementary information content facilitates the substitution of the descriptive mapping with diagnosis, in the sense that it contributes to the application of trait-based monitoring, better characterization of the state of the habitat and biodiversity trends, the earlier identification of stress and disturbance, and more precise tracking of water and soil components that are pertinent to environmental risk. Combined with sound preprocessing and physically-explainable modeling, hyperspectral measurements can provide indicators that are of close interest to the management: they will tell where the change is happening, help elucidate potential causes, and justify intervention priorities and evaluation.

Simultaneously, the review points out that the sustainability impact is defined not so much by the individual methodological improvements but by the sense of integrity of the entire sensor-to-product pipeline. The retrieval models are built on platform enhancements, harmonization of cross-sensors, atmospheric and geometric correction, mitigation of artifacts, as well as the appropriate representation of features. Each of the empirical learning, physics-based inversion, unmixing frameworks, and deep learning methods has its own benefits; however, they are all susceptible to the same systemic drawbacks: domain shift across ecosystems and season mixed pixels, scale mismatch, and preprocessing spectral biases that can mimic ecological information. It has been proposed that data fusion is a viable solution to ambiguity reduction and operational strength, especially where hyperspectral data is processed with LiDAR-generated structure, SAR sensitivity to moisture, and all-weather and thermal limits can be addressed due to stress and energy balance. Fusion, however, also enhances the requirement to be careful in co-registration and propagation of uncertainty, and is fundamental to the need to have transparent QA/QC since error propagation may happen across modes.

One of the key findings of this article is that the decision-ready hyperspectral products should be based on trustworthiness. To the managers and users of the policy, the map of a trait or a constituent can be as helpful as it is reliable for operating in ecological conditions and explaining itself. Uncertainty quantification and out-of-distribution-detecting, and physically grounded interpretability are thus not features that can be specified as optional, but this is mandatory. Similarly, validation should be able to develop into a multi-site and multi-season testing, with standardized field protocols and sustained observation networks that are more representative of the variety of conditions in which the products will be used. In the absence of these components, the hyperspectral remote sensing would result in spectacular demonstrations that cannot be converted into reliable or reportable services.

In the future, it can be seen that there are a few paths that one can take to challenge the frontiers of sustainability. The hybrid physical-machine approach to learning presents an interesting path to a better transferability, that is, radiative transfer restrictions are imposed, but with the flexibility of current-day learning. Pretraining itself and emerging preliminary representations of spectra can diminish reliance on labeled data and enhance per geographic and sensor diversities as long as such models fall under delivered records and stringent cross-domain information testing. Further progress towards data format analysis-ready and cloud-native processing and benchmarking predictability will reduce adoption barriers as well as allow consistent regional-to-global products. The social and institutional aspect is also very critical: the co-design of the stakeholders, the understanding of the restrictions of the product, and equity in the access to data and strategies will determine the possibility of making imaging spectroscopy a useful stewardship and risk-reduction tool.

To conclude, hyperspectral remote sensing will be a transformative tool in the management of ecosystems and

natural resources when it comes to more specific, earlier, and more mechanistically-based monitoring of the state of the environmental condition and change. To achieve this potential at a big scale necessarily entails concerted advances in harmonization, validation, uncertainty-sensitive modeling, and operation delivery. When these priorities are achieved, imaging spectroscopy would form part of sustainable intelligence-assisting timely interventions, enhancing accountability in the restoration and compliance, and raising the capability of the society to manage ecosystems and natural resources in conditions of increased global change.

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