Hyperspectral Drone-Based Remote Sensing for Assessing Post-Fire Soil Recovery: Spectral Indices, Soil Properties, and Vegetation Regeneration Monitoring in Burned Ecosystems

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Abstract

Wildfires increasingly threaten soil integrity worldwide, causing organic matter loss, altered hydrological properties, enhanced erosion susceptibility, and disrupted nutrient cycling that can persist for years to decades. Traditional field-based assessments and satellite remote sensing provide limited spatial resolution or temporal flexibility for tracking rapid post-fire soil recovery dynamics at management-relevant scales. Hyperspectral imaging mounted on unmanned aerial vehicles (UAVs) has emerged as a transformative approach for high-resolution monitoring of burn severity impacts and subsequent soil regeneration processes. This review synthesizes recent advances in drone-based hyperspectral remote sensing for post-fire soil recovery assessment, emphasizing sensor technologies, spectral indices derivation, and soil property estimation methodologies. We examine key hyperspectral platforms including Headwall Nano-Hyperspec, Specim AFX, and HySpex sensors deployed on multirotor and fixed-wing UAVs for mapping soil charring, moisture content, organic carbon changes, and erosion risk across burned landscapes. Applications of visible-near-infrared and shortwave-infrared spectral indices for burn severity classification, coupled with machine learning algorithms for predictive modeling of soil properties and vegetation regeneration trajectories, are critically evaluated through Mediterranean, boreal, and peatland case studies. Despite promising results, challenges including atmospheric correction complexities, data processing demands, and operational constraints require continued innovation. Future directions encompass enhanced spectral-spatial fusion techniques, real-time processing capabilities, and integration with climate models for adaptive post-fire ecosystem management.

Keywords: Hyperspectral imaging; UAV remote sensing; Post-fire soil recovery; Burn severity indices; Vegetation regeneration; Soil properties monitoring

Introduction

Wildfires represent one of the most disruptive disturbances to terrestrial ecosystems, with profound and lasting impacts on soil physical, chemical, and biological properties. Fire-induced alterations include combustion of soil organic matter, formation of water-repellent layers, modification of aggregate stability, and dramatic changes in surface albedo and moisture retention capacity [1, 2]. These transformations cascade through ecosystem processes, influencing erosion rates, nutrient availability, microbial community structure, and vegetation reestablishment dynamics. As climate change intensifies fire regimes globally, understanding and monitoring post-fire soil recovery has become critical for ecosystem management, restoration planning, and erosion control interventions [3, 4].

Traditional approaches to post-fire soil assessment rely predominantly on field sampling campaigns and laboratory analyses that, while providing accurate point measurements, are labor-intensive, spatially limited, and often conducted weeks to months after fire events when critical early-stage recovery processes have already progressed [5]. Satellite-based remote sensing platforms, including Landsat, Sentinel-2, and MODIS, have enabled broad-scale burn severity mapping through multispectral indices such as the Normalized Burn Ratio (NBR) and differenced NBR (dNBR) [6, 7]. However, these systems typically operate at spatial resolutions of 10-30 meters or coarser, insufficient for capturing the fine-scale heterogeneity characteristic of post-fire landscapes where soil properties and vegetation recovery can vary dramatically over meter-scale distances [8].

The advent of hyperspectral imaging systems mounted on unmanned aerial vehicles has created unprecedented opportunities for bridging the gap between field-based precision and satellite-based synoptic coverage. Drone-based hyperspectral sensors acquire data across hundreds of contiguous narrow spectral bands spanning visible, near-infrared (VNIR), and shortwave-infrared (SWIR) regions at spatial resolutions of centimeters to decimeters [9, 10]. This combination of high spectral and spatial resolution enables detailed characterization of soil surface properties, detection of subtle spectral signatures associated with charring intensity, moisture gradients, and organic matter content, and tracking of vegetation regeneration at ecologically meaningful scales [11, 12]. Furthermore, the operational flexibility of UAV platforms permits repeated surveys at user-defined intervals, facilitating multitemporal analysis of recovery trajectories during critical post-fire periods when soil conditions evolve rapidly [13].

This review synthesizes current knowledge on hyperspectral drone-based remote sensing for post-fire soil recovery assessment, with emphasis on sensor technologies, spectral analysis methodologies, soil property retrieval algorithms, and vegetation regeneration monitoring. We examine how integration of machine learning approaches with drone hyperspectral data enhances predictive capabilities for soil condition mapping and evaluate applications across diverse ecosystem types affected by recent wildfire events. The scope encompasses sensor platforms and preprocessing workflows, spectral indices and mechanisms for burn severity and soil assessment, regional case studies demonstrating operational applications, and critical analysis of limitations and future research directions.

2. Hyperspectral Drone Systems and Data Acquisition

2.1. UAV Platforms and Hyperspectral Sensors

Contemporary hyperspectral imaging for post-fire applications relies on integration of specialized sensors with multirotor or fixed-wing UAV platforms, each offering distinct operational advantages. Multirotor systems, particularly hexacopters and octocopters, provide vertical takeoff and landing capabilities, stable hovering for precise georeferencing, and adaptability to complex terrain typical of burned landscapes [14]. Fixed-wing platforms enable extended flight durations and coverage of larger burned areas, though requiring suitable launch and landing zones that may be scarce in freshly burned terrain [15].

Leading hyperspectral sensors deployed for post-fire soil monitoring include the Headwall Nano-Hyperspec series, offering 270+ spectral bands across 400-1000 nm with spatial resolutions achievable below 5 cm from typical UAV altitudes [16]. The Specim AFX hyperspectral cameras provide pushbroom imaging across VNIR (400-1000 nm) and SWIR (1000-2500 nm) ranges, enabling detection of absorption features related to soil moisture, clay minerals, and organic compounds [17]. HySpex Mjolnir sensors integrate dual VNIR-SWIR imaging with high signal-to-noise ratios critical for discriminating subtle spectral variations in fire-affected soils [18]. Emerging systems such as the Resonon Pika series and Cubert UHD185 offer increasingly compact form factors suitable for small multirotor platforms while maintaining spectral fidelity [19].

The selection of sensor-platform combinations depends on project-specific requirements balancing spatial coverage, spectral range priorities, ground sample distance targets, and logistical constraints. Post-fire soil assessment particularly benefits from SWIR capabilities for detecting water absorption features near 1400 nm, 1900 nm, and diagnostic absorption bands for soil organic matter and charcoal around 2200 nm [20]. Flight planning considerations include maintaining consistent altitude and speed for uniform spatial resolution, ensuring adequate overlap (typically 60-80%) for mosaicking, and timing acquisitions relative to soil moisture conditions and vegetation phenology [21].

2.2. Data Preprocessing and Calibration Techniques

Raw hyperspectral datacubes from UAV acquisitions require systematic preprocessing to convert sensor digital numbers into calibrated reflectance values suitable for spectral analysis and index derivation. Radiometric calibration transforms raw radiance measurements using laboratory-determined calibration coefficients specific to each sensor [22]. Geometric correction addresses spatial distortions arising from platform motion, terrain relief, and sensor viewing geometry through integration of onboard GPS/IMU data with ground control points or direct georeferencing approaches [23].

Atmospheric correction represents a particularly critical step for UAV hyperspectral data, as even at low flight altitudes, atmospheric scattering and absorption can significantly affect spectral signatures. Empirical line calibration methods, utilizing in-field reflectance panels deployed within the scene, provide computationally efficient correction suitable for single-flight campaigns [24]. Physically-based radiative transfer models such as ATCOR-4 and FLAASH, while developed primarily for airborne platforms, can be adapted for UAV applications when atmospheric composition and aerosol loading parameters are constrained [25]. The prevalence of smoke, ash, and particulate matter in post-fire environments introduces additional complexities requiring careful quality control and potential scene-specific correction strategies [26].

Spectral smoothing and denoising procedures reduce sensor noise while preserving diagnostic absorption features, commonly implemented through Savitzky-Golay filtering or wavelet-based approaches [27]. Mosaicking of individual flight lines into spatially continuous products employs feathering algorithms to minimize seam artifacts while maintaining spectral consistency [28]. Increasingly, automated processing pipelines integrate these steps within unified workflows, reducing manual intervention and enabling near-real-time data delivery for time-sensitive post-fire assessment applications [29].

2.3. Emerging Integrated Approaches

The synergistic integration of hyperspectral UAV data with complementary information sources and advanced analytical frameworks represents a frontier in post-fire monitoring capabilities. Fusion of hyperspectral imagery with high-resolution RGB orthomosaics and digital surface models from structure-from-motion photogrammetry provides combined spectral-spatial-structural characterization of burned terrain [30]. This enables simultaneous assessment of topographic controls on erosion risk, vegetation structural recovery, and spectral indicators of soil condition.

Machine learning algorithms, particularly random forests, support vector machines, and deep convolutional neural networks, increasingly underpin spectral analysis workflows for post-fire applications. These approaches learn complex nonlinear relationships between hyperspectral signatures and soil properties from training datasets, enabling predictive mapping across entire surveyed areas [31, 32]. Transfer learning strategies allow models trained in one geographic region or ecosystem type to be adapted for application in data-scarce environments, accelerating deployment of monitoring capabilities following newly-occurred fires [33].

Multitemporal hyperspectral acquisitions throughout post-fire recovery periods, when analyzed through change detection algorithms and trajectory analysis frameworks, reveal dynamics of soil property evolution and vegetation recolonization that single-date surveys cannot capture [34]. Time series approaches identify thresholds in recovery processes, detect stalled or degraded recovery trajectories requiring intervention, and quantify rates of change in key soil and vegetation parameters [35]. Cloud-based processing platforms and edge computing solutions are beginning to enable field-deployable analysis capabilities, bringing sophisticated spectral interpretation tools directly to fire management personnel.

3. Mechanisms for Assessing Post-Fire Soil Recovery

3.1. Spectral Indices for Burn Severity and Soil Charring

Spectral vegetation indices originally developed for satellite platforms have been adapted and refined for hyperspectral UAV applications in burn severity assessment. The Normalized Burn Ratio (NBR), calculated as (NIR - SWIR) / (NIR + SWIR) using bands near 850 nm and 2200 nm, remains foundational for mapping burn severity by exploiting the contrasting reflectance changes of vegetation and exposed soil following fire. The Relativized Burn Ratio (RBR), normalizing dNBR by pre-fire NBR values, provides improved performance in ecosystems with varying pre-fire vegetation density.

Hyperspectral data enables derivation of novel indices specifically targeting soil charring and ash deposition. The Char Soil Index (CSI), utilizing the distinctive low reflectance of charred surfaces across visible to SWIR wavelengths combined with specific absorption features, discriminates charring intensity levels corresponding to different fire temperatures and residence times. The Ash Index, leveraging increased reflectance in visible bands and specific spectral signatures near 550 nm, quantifies ash layer thickness and persistence, which influences albedo, water infiltration, and nutrient availability.

The Soil-Adjusted Vegetation Index (SAVI) and its modifications incorporate a soil brightness correction factor particularly valuable in sparsely vegetated post-fire environments where mixed soil-vegetation pixels dominate. Hyperspectral variants enable optimization of soil adjustment parameters for specific soil types and moisture conditions prevalent in burned landscapes. Indices targeting specific minerals and soil constituents, such as iron oxide ratios and clay mineral indices, track fire-induced mineralogical transformations and subsequent weathering processes during recovery.

3.2. Estimation of Soil Properties

Hyperspectral remote sensing enables non-destructive estimation of critical soil properties governing post-fire recovery trajectories. Soil moisture content, fundamental to erosion risk, microbial activity, and vegetation reestablishment, exhibits diagnostic absorption features in SWIR bands near 1400 nm and 1900 nm where water molecules strongly absorb radiation. The Normalized Soil Moisture Index (NSMI) and variants specifically designed for burned soils account for char and ash interference with moisture signals. Validation studies demonstrate estimation accuracies for surface soil moisture within 3-5% volumetric water content when calibrated to local soil types.

Soil organic matter and carbon content, dramatically reduced by fire and critical for recovery processes, generate subtle absorption features across visible to SWIR wavelengths related to organic compound molecular structures. Machine learning regression models relating hyperspectral signatures to laboratory-measured organic carbon achieve prediction accuracies with R^2 values of 0.7-0.85 in post-fire contexts. These models enable mapping of organic matter recovery trajectories as vegetation litter accumulates and soil biological activity regenerates organic pools.

Fire-induced water repellency, created by volatilization and downward migration of hydrophobic organic compounds during heating, profoundly affects infiltration and erosion. Spectral detection of water repellency remains challenging due to its subsurface nature, but surface indicators including specific clay mineral alterations and char characteristics correlated with repellency development show promise for indirect assessment. Erosion susceptibility indices combine spectral indicators of bare soil extent, surface roughness from co-acquired elevation data, soil moisture, and aggregate stability proxies to map relative erosion risk across burned watersheds.

3.3. Monitoring Vegetation Regeneration and Soil-Vegetation Interactions

Vegetation regeneration represents both a key indicator and driver of soil recovery following fire. Hyperspectral UAV data enables detailed tracking of plant recolonization patterns, species composition shifts, and functional trait distributions that influence soil stabilization, organic matter inputs, and hydrological processes. The Enhanced Vegetation Index (EVI) and Normalized Difference Vegetation Index (NDVI), calculated at high spatial resolution from hyperspectral data, map progressive increases in photosynthetic biomass with sensitivities to early-stage seedling emergence undetectable in satellite imagery.

Hyperspectral discrimination of plant functional types and species, achieved through analysis of leaf biochemical composition signatures, reveals successional dynamics and identifies native versus invasive colonization patterns. This information guides restoration interventions targeting promotion of desired species assemblages. Spectral traits related to leaf nitrogen content, lignin, and cellulose provide insights into vegetation quality for nutrient cycling and litter decomposition processes.

The bidirectional coupling between vegetation recovery and soil condition evolution can be analyzed through integrated spectral indices and spatial pattern analysis. Vegetation patches create microsites with enhanced soil moisture retention, organic matter accumulation, and reduced erosion, detectable as correlated spatial patterns in soil and vegetation spectral signatures. Temporal analysis of these coupled dynamics reveals positive feedbacks accelerating recovery in favorable microsites and identifies stalled recovery zones where soil degradation limits vegetation reestablishment, potentially requiring active restoration.

4. Regional Applications and Case Studies

4.1. Mediterranean and European Regions

Mediterranean ecosystems, characterized by summer droughts and fire-adapted vegetation communities, have been focal regions for hyperspectral UAV applications in post-fire assessment. Following extensive wildfires in Greece during 2018-2021, drone-mounted Specim AFX sensors mapped burn severity gradients in pine and mixed forests, revealing fine-scale patterns of soil charring intensity linked to topographic position and pre-fire fuel loads. Multitemporal surveys tracked soil moisture recovery trajectories over two years, identifying persistent dry zones at high erosion risk requiring targeted stabilization treatments.

Portuguese cork oak and eucalyptus forests burned in 2017 wildfires provided testing grounds for machine learning integration with hyperspectral data. Random forest models trained on field-measured soil organic carbon and hyperspectral signatures achieved prediction accuracies of $R^2 = 0.81$, enabling watershed-scale mapping of carbon loss and subsequent regeneration. These maps informed prioritization of erosion control measures and quantification of fire impacts on regional carbon budgets.

Spanish Mediterranean shrublands affected by 2019-2022 fires demonstrated applications of vegetation functional type discrimination for assessing recovery trajectories. Hyperspectral UAV surveys discriminated resprouting woody species from herbaceous colonizers and invasive grasses, revealing divergent post-fire successional pathways with implications for long-term soil protection and ecosystem services. Integration with soil moisture and organic matter maps identified locations where unfavorable soil conditions limited desired woody species regeneration.

4.2. Boreal, Peatland, and Other Vulnerable Ecosystems

Boreal forest fires, which can consume deep organic soil horizons in addition to vegetation, present distinct monitoring challenges addressed through hyperspectral approaches. Following 2019 fires in Canadian boreal regions, Headwall Nano-Hyperspec sensors on fixed-wing UAVs mapped combustion depths and residual organic layer thickness through spectral signatures of exposed mineral soils and char characteristics. These measurements, validated against field excavations, predicted post-fire hydrological changes and permafrost vulnerability with management implications for northern ecosystems.

Peatland fires represent particularly severe soil degradation scenarios where smoldering combustion can consume centuries of accumulated organic matter. Indonesian and Malaysian peatland fires surveyed with HySpex sensors in 2020-2023 utilized SWIR bands to discriminate ash composition, remaining peat properties, and water table position influences on spectral signatures. Multitemporal monitoring documented gradual revegetation by grasses and shrubs and associated peat accumulation initiation, though recovery timescales of decades to centuries were evident from slow spectral trajectory changes.

Australian eucalyptus forests and grasslands burned in 2019-2020 "Black Summer" fires provided case studies for ash mapping and erosion risk assessment. Hyperspectral indices distinguished thick ash deposits from thin ash layers and bare soil, with implications for post-fire water quality as rains mobilized ash nutrients. Coupled vegetation recovery monitoring identified rapid grass colonization providing soil stabilization within months, contrasting with slower woody vegetation reestablishment.

5. Challenges and Future Perspectives

5.1. Data Processing and Technical Limitations

Despite rapid technological advances, hyperspectral UAV systems face significant data processing challenges. Individual flight campaigns generate datacubes exceeding hundreds of gigabytes, requiring substantial computational resources and storage infrastructure. Processing workflows from raw data to analysis-ready products remain time-intensive, often requiring days to weeks of analyst effort, limiting operational deployment for rapid post-fire assessment where timely information is critical.

Atmospheric correction uncertainties, particularly in smoke and ash-laden post-fire environments, introduce spectral errors that propagate through index calculations and property estimations. Validation studies indicate reflectance uncertainties of 5-15% in challenging atmospheric conditions, degrading soil property prediction accuracies. Development of robust correction algorithms specifically adapted to post-fire atmospheric conditions and incorporation of real-time atmospheric measurements from UAV-mounted sensors represent active research frontiers.

Spatial and spectral resolution tradeoffs constrain system design choices. Achieving centimeter-scale spatial resolution requires low flight altitudes reducing coverage area per flight, while broader coverage necessitates coarser resolution potentially averaging fine-scale heterogeneity. Spectral resolution similarly trades channel bandwidth against signal-to-noise ratios, with narrower bands providing finer discrimination of absorption features but reduced photon counts, particularly problematic for the dark surfaces of charred soils.

5.2. Scalability, Cost, and Operational Barriers

The capital costs of hyperspectral sensors remain substantial, with systems suitable for research-grade post-fire assessment ranging from 50,000 to 200,000 USD, prohibitive for many land management agencies. UAV platform costs, pilot training requirements, and data processing expertise further elevate operational barriers. While rental models and imaging service providers offer alternatives to direct ownership, sustainable business models for operational post-fire monitoring programs remain nascent.

Regulatory frameworks governing UAV operations create logistical constraints, particularly for large burned area coverage requiring flights beyond visual line of sight or over sensitive ecosystems. Authorization processes can require weeks to months, potentially missing critical early post-fire assessment windows. International variations in regulations complicate deployment of standardized monitoring protocols across regions. Evolving regulations increasingly accommodate expanded UAV operations, but harmonization and streamlining remain needed.

Scalability challenges emerge when attempting watershed to landscape-scale coverage commensurate with fire extents.

Individual UAV flights cover areas of hectares to a few square kilometers, requiring numerous flights for large burns. Coordination of multiple platforms, standardization of data acquisition protocols, and mosaicking of datasets from different dates and atmospheric conditions introduce quality control complexities. Integration of UAV hyperspectral sampling with complementary satellite monitoring offers hybrid approaches balancing coverage and resolution.

5.3. Future Directions

Advances in sensor miniaturization and emerging technologies promise to address current limitations. Compact snapshot hyperspectral cameras eliminating pushbroom motion artifacts, sensor arrays enabling simultaneous multispectral and hyperspectral acquisition, and integration of thermal infrared bands for soil moisture and temperature monitoring represent near-term developments. Quantum cascade laser-based active hyperspectral systems may overcome signal limitations for dark charred surfaces.

Real-time onboard processing leveraging increasingly capable embedded computing and artificial intelligence hardware could enable in-flight data reduction and priority target identification, optimizing flight paths and reducing data volumes. Cloud-based automated processing pipelines with user-friendly interfaces accessible to fire managers without remote sensing expertise would democratize technology access. Open-source software ecosystems and standardized data formats facilitate broader adoption and collaborative algorithm development.

Integration of hyperspectral UAV monitoring within broader earth observation frameworks combining satellite time series, ground sensor networks, and process-based ecosystem models enables multiscale synthesis of post-fire recovery dynamics. Assimilation of hyperspectral-derived soil property maps into hydrological and erosion models improves prediction of post-fire watershed responses. Coupling with climate projections and fire regime models supports proactive identification of ecosystems at risk for severe fire impacts and impaired recovery under future conditions.

Emerging applications include detection of invasive species colonization in post-fire environments, assessment of belowground soil biodiversity recovery through surface spectral proxies, and quantification of smoke and ash deposition impacts on unburned adjacent areas. Integration with autonomous ground vehicles for coordinated air-ground hyperspectral sampling and validation could enhance spatial coverage and measurement accuracy. Ultimately, hyperspectral UAV technologies are transitioning from research tools to operational assets for adaptive post-fire ecosystem management.

6. Tables

Table 1: Major hyperspectral sensors and UAV platforms used for post-fire soil and vegetation recovery studies

Sensor System	Spectral Range (nm)	Spectral Resolution	Spatial Resolution	Key Features	Example Applications
Headwall Nano-Hyperspec	400-1000	270+ bands, 2.2 nm	2-10 cm	Compact, high SNR, integrated GPS/IMU	Burn severity mapping, ash detection, vegetation recovery
Specim AFX	VNIR: 400-1000; SWIR: 1000-2500	224-256 bands	5-15 cm	Dual-range capability, soil moisture sensitivity	Soil organic matter estimation, moisture mapping
HySpex Mjolnir	VNIR: 400-1000; SWIR: 1000-2500	480 combined bands	3-20 cm	High radiometric accuracy, dual cameras	Detailed soil property retrieval, mineralogy
Resonon Pika L	400-1000	281 bands, 2.1 nm	5-12 cm	Lightweight (0.6 kg), multirotor compatible	Small-area intensive monitoring, validation studies
Cubert UHD185	450-950	125 bands, 4 nm	4-8 cm	Snapshot acquisition, no motion artifacts	Rapid assessment, temporal dynamics

Table 2: Spectral indices and bands commonly derived from drone hyperspectral data for post-fire burn severity, soil properties, and recovery assessment

Index/Band	Formula/Wavelength	Target Parameter	Mechanism	Typical Accuracy
Normalized Burn Ratio (NBR)	(NIR850 - SWIR2200) / (NIR850 + SWIR2200)	Burn severity	Vegetation loss, soil exposure contrast	High severity detection: >85%
Relativized Burn Ratio (RBR)	dNBR / (NBR_prefire + 1.001)	Normalized severity	Accounts for pre-fire vegetation density	Improved in heterogeneous vegetation
Char Soil Index (CSI)	Custom ratio using VIS-SWIR reflectance minima	Charring intensity	Low reflectance of charcoal across spectrum	Charring depth correlation: $R^2 = 0.72$
Normalized Soil Moisture Index (NSMI)	(SWIR1400 - SWIR1900) / (SWIR1400 + SWIR1900)	Soil moisture	Water absorption bands	±3-5% volumetric moisture
Soil-Adjusted Vegetation Index (SAVI)	1.5 × (NIR - Red) / (NIR + Red + 0.5)	Vegetation cover in sparse conditions	Soil brightness correction	Early regeneration detection
Organic Matter Index	SWIR absorption near 2200 nm + visible reflectance	Soil organic carbon	Organic compound absorption features	Prediction $R^2 = 0.70\text{-}0.85$
Ash Index	Visible reflectance peak ~550 nm	Ash layer thickness	High ash reflectance, specific spectral shape	Thickness classes: 80% accuracy
Iron Oxide Ratio	Red630 / Blue480	Fire-induced oxidation	Enhanced iron oxide formation from heating	Mineralogical change indicator

Table 3: Case studies and regional applications of hyperspectral drone data in post-fire soil recovery monitoring

Region/Ecosystem	Fire Event	Sensor System	Key Soil/Vegetation Parameters	Main Findings	Reference Context
Greek pine forests	2018-2021 wildfires	Specim AFX	Burn severity, soil moisture trajectories	Fine-scale severity patterns linked to topography; persistent dry zones identified	Mediterranean applications
Portuguese cork oak/eucalyptus	2017 wildfires	Headwall + ML models	Soil organic carbon loss/recovery	SOC prediction $R^2 = 0.81$; carbon budget quantification	Machine learning integration
Spanish Mediterranean shrublands	2019-2022 fires	Custom hyperspectral UAV	Vegetation functional types, soil-plant interactions	Divergent successional pathways; soil limitations on woody regeneration	Vegetation discrimination
Canadian boreal forests	2019 fires	Headwall on fixed-wing	Organic layer combustion depth, exposed mineral soil	Combustion depth mapped; permafrost vulnerability assessed	Boreal applications
Indonesian/Malaysian peatlands	2020-2023 fires	HySpex SWIR	Peat properties, water table position, ash composition	Century-scale recovery timelines evident; slow spectral changes	Peatland severe degradation
Australian eucalyptus/grasslands	2019-2020 Black Summer	Multiple sensors	Ash distribution, erosion risk, rapid grass colonization	Thick ash deposits mapped; rapid stabilization by grasses	Ash mapping, erosion assessment

Table 4: Advantages, limitations, and translational challenges of hyperspectral drone-based approaches for post-fire soil recovery assessment

Aspect	Advantages	Limitations	Translational Challenges
Spatial Resolution	Centimeter-scale detail captures fine heterogeneity; detects early vegetation colonization	Limited coverage per flight (hectares to few km²); mosaic complexity for large fires	Balancing resolution vs. coverage; standardizing multi-flight protocols
Spectral Resolution	Hundreds of narrow bands enable subtle soil property discrimination; diagnostic absorption features	Large data volumes; processing intensity; reduced SNR in narrow bands	Real-time processing development; analyst training requirements
Temporal Flexibility	User-defined repeat intervals; captures rapid early recovery dynamics	Weather/regulatory delays; consistent atmospheric conditions difficult	Operational protocols for standardized temporal sampling
Soil Property Estimation	Non-destructive; spatially continuous; multiple properties simultaneously	Surface-only measurements; influenced by ash/vegetation cover; calibration requirements	Transfer learning across regions; validation dataset development
Operational Deployment	Rapid mobilization potential; targeted sampling of priority areas	High capital costs (50-200K USD); pilot certification; data expertise needs	Sustainable operational models; regulatory harmonization
Integration Potential	Synergy with RGB, thermal, LiDAR; machine learning enhancement	Fusion complexities; geometric co-registration; computational demands	Automated pipelines; user-friendly interfaces for managers
Accuracy & Validation	High accuracy when calibrated (e.g., moisture ±3-5%, SOC $R^2>0.7$)	Atmospheric correction uncertainties (5-15% in smoke); ash interference	Robust correction algorithms for post-fire atmospheres

7. Figure

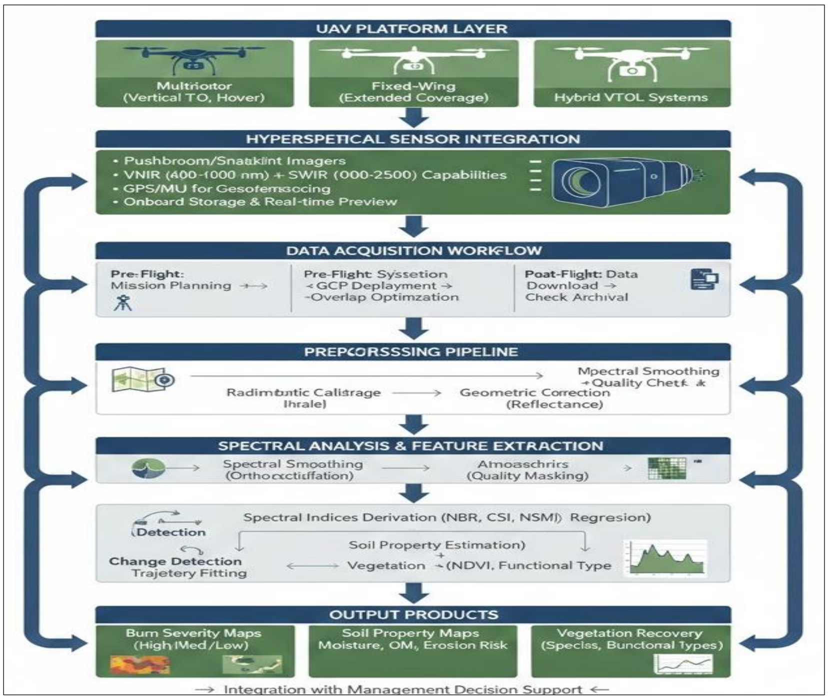
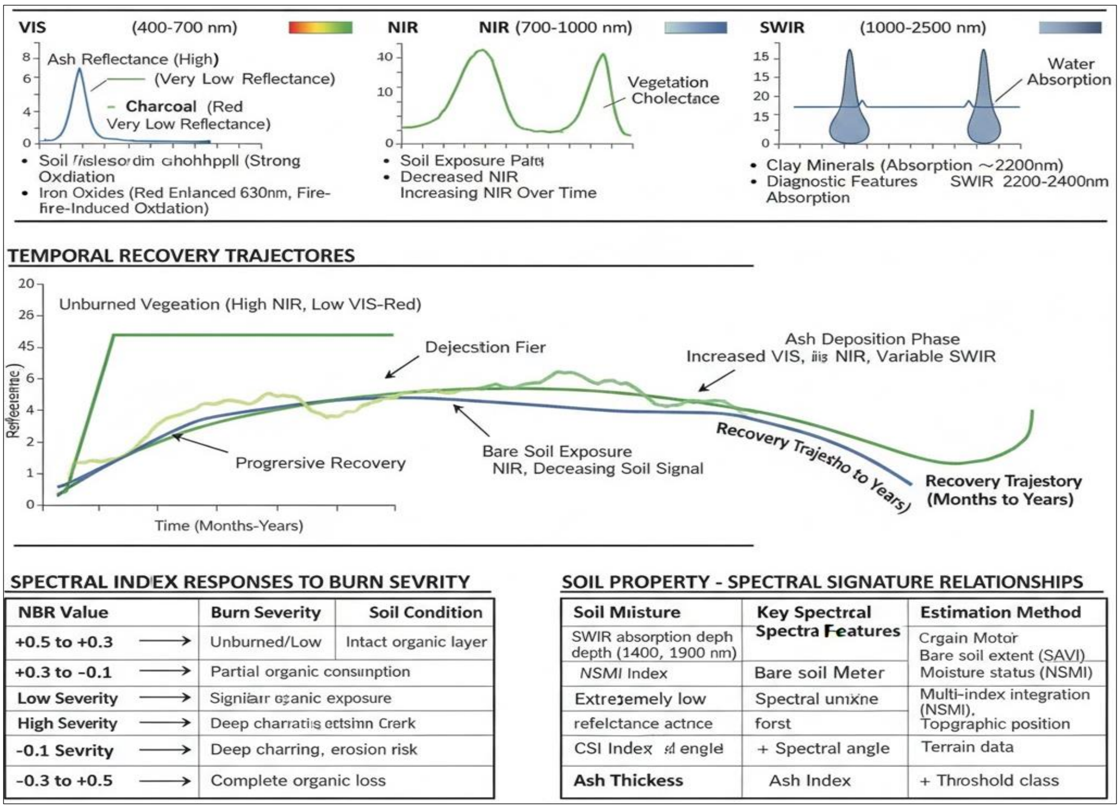


Fig 1: Architecture of hyperspectral drone systems for post-fire soil recovery assessment



NBR Value		Burn Severity	Soil Condition
+0.5 to +0.3	⟶	Unburned/Low	Intact organic layer
+0.3 to -0.1	⟶	Partial organic consumption	
Low Severity	⟶	Signiiarr ogganic exposure	
High Severity	⟶	Deep charratis ectsinn Crerk	
-0.1 Sevrity	⟶	Deep charring, erosion risk	
-0.3 to +0.5	⟶	Complete organic loss	

Soil Miisture	Key Spectrcal Spectra Features	Estimation Method
SWIR absorption deph depth (1400, 1900 nm)		Crgain Motor Bare soil extent (SAVI)
NSMI Index	Bare soil Meter	Moisture status (NSMI)
Extrejemely low	Spectral unixne	Multi-index integration (NSMI).
refelctance actnce	forst	Topgraphic position
CSI Index el engle	+ Spectral angle	Terrain data
Ash Thickess	Ash Index	+ Throshold class

Fig 2: Key mechanisms and spectral features in hyperspectral monitoring of post-fire soil and vegetation recovery

8. Conclusion

Hyperspectral drone-based remote sensing has emerged as a powerful approach for high-resolution monitoring of post-fire soil recovery dynamics, bridging critical gaps between field-based precision and satellite-based coverage. The integration of advanced UAV platforms with sophisticated hyperspectral sensors enables detailed characterization of burn severity, soil property changes, and vegetation regeneration at spatiotemporal scales directly relevant to ecosystem management and restoration decision-making. Spectral indices derived from hundreds of contiguous wavelength bands provide unprecedented sensitivity to subtle variations in soil charring, organic matter content, moisture status, and erosion susceptibility that drive recovery trajectories in burned landscapes.

Applications across Mediterranean, boreal, peatland, and other fire-affected ecosystems demonstrate the operational value of hyperspectral UAV monitoring for informing targeted interventions, tracking restoration effectiveness, and understanding soil-vegetation coupling processes. Machine learning integration enhances predictive capabilities for soil property mapping from spectral signatures, while multitemporal analysis reveals recovery dynamics undetectable through single-date assessments. Despite remaining challenges in data processing efficiency, atmospheric correction accuracy, and operational scalability, ongoing technological advances and analytical innovations continue expanding capabilities.

Future development priorities include real-time processing workflows, cost reduction through sensor miniaturization, regulatory framework evolution supporting expanded operational deployment, and integration within multiscale earth observation systems. As wildfire regimes intensify globally under climate change, hyperspectral drone remote sensing represents an essential technology for monitoring ecosystem resilience, guiding adaptive management, and supporting evidence-based policy for post-fire landscape recovery. Continued interdisciplinary collaboration among remote sensing scientists, fire ecologists, soil scientists, and land managers will accelerate translation of technological capabilities into sustained societal benefits.

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