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Review of Noise Removal in Passive Remote Sensing: Comparative MSI vs HSI Perspectives with Indian Case Studies

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Abstract: The proliferation of passive remote sensing (RS) missions particularly multispectral (MSI) and hyperspectral (HSI) sensors has enabled wide-ranging applications in agriculture, water resources, urban monitoring, and climate studies. However, the presence of noise arising from atmospheric effects, sensor calibration errors, striping, Gaussian disturbances, and mixed pixels significantly degrades image quality, limiting the accuracy of downstream tasks such as feature extraction, classification, and spectral unmixing. While substantial research has focused on classification and dimensionality reduction, comparatively fewer efforts have systematically reviewed noise mitigation strategies. This review provides a comprehensive analysis of noise removal techniques in passive RS, spanning statistical filtering, band selection, ensemble learning, and advanced machine learning (ML) and deep learning (DL) approaches, including recent transformer-based architectures. We emphasize the comparative impact of noise in MSI versus HSI data as well as highlight Indian case studies with open datasets (Resourcesat, Cartosat, HySIS, Sentinel-2), and analyze emerging trends such as semi-supervised learning and multimodal fusion. By integrating classical methods with modern ML pipelines, this review offers a structured perspective on challenges, progress, and future research directions for robust and noise-resilient passive RS applications.
Keywords: Multispectral Imaging, Hyperspectral Imaging, Noise sensitivity, Spectral bands (broad vs. narrow), Reflectance variation, Spectral discrimination.

I. INTRODUCTION

Passive remote sensing (RS) systems, particularly multispectral imaging (MSI) and hyperspectral imaging (HSI), have become indispensable for Earth observation and environmental monitoring. MSI sensors such as Sentinel-2 and Resourcesat capture tens of spectral bands, enabling efficient large-scale land use and vegetation mapping. In contrast, HSI sensors such as NASA's AVIRIS and India's HySIS provide hundreds of contiguous narrow bands, allowing detailed material characterization and subtle discrimination of vegetation stress, soil properties, and water quality. Foundational works such as Richards and Jia (2006) and Goetz et al. (1985) established the theoretical and practical advantages of MSI and HSI, highlighting their broad applications in agriculture, forestry, and climate science. However, their operational utility depends heavily on the quality of the acquired data, which is often degraded by noise.

Though passive remote sensing (RS) has become a cornerstone of Earth observation, providing critical data for agriculture, water resources, climate monitoring, and urban studies and this rich spectral information enables detailed characterization of land cover, vegetation stress, and environmental processes (Richards & Jia, 2006; Goetz et al., 1985). The contamination of data by multiple noise sources, including atmospheric interference, sensor calibration errors, striping, Gaussian disturbances, and mixed pixels. Such degradations reduce classification accuracy and complicate tasks such as spectral unmixing and feature extraction (Plaza et al., 2009; Zheng et al., 2021).

Much of the existing literature has focused on classification and feature extraction, while comparatively fewer studies have comprehensively reviewed noise mitigation approaches. For instance, machine learning methods have been widely applied for classification in RS, ranging from support vector machines and random forests to deep learning, but these works often treat noise as a secondary concern (Maxwell et al., 2018; Grewal et al., 2023).

To address this gap, we focused on the review of noise removal techniques in passive RS, covering statistical filtering, band selection, ensemble learning, and modern machine learning and deep learning approaches. Classical studies demonstrated the robustness of support vector machines (Melgani & Bruzzone, 2004) and random forests (Ham et al., 2005) for noisy high-dimensional data, while recent work has emphasized spectral– spatial deep networks and transformer-based architectures for noise-resilient classification (Grewal et al., 2023).

In addition to surveying global developments, we aim to highlight the comparative impacts of noise in MSI versus HSI, review state-of-the-art mitigation strategies, and outline future research directions. This paper emphasizes Indian case studies where open datasets such as Resourcesat, Cartosat, and HySIS play a critical role. Semi-supervised learning strategies tailored to Indian hyperspectral imagery (Dhekane et al., 2021) and crop-specific classification studies (Kambli & Palkar, 2024) illustrate the importance of noise handling in practical applications.

II. PASSIVE REMOTE SENSING FUNDAMENTALS

Passive remote sensing relies on sensors that capture solar radiation reflected from the Earth’s surface, with multispectral imaging (MSI) and hyperspectral imaging (HSI) being the two dominant modalities. MSI sensors, such as Sentinel-2 MSI and Resourcesat-2 LISS-III, acquire tens of broad spectral bands across the visible to shortwave infrared regions. This enables efficient large-scale monitoring of vegetation, land use, and water resources with manageable data volumes. In contrast, HSI sensors, such as NASA’s AVIRIS and India’s HySIS, collect hundreds of contiguous narrow spectral bands, providing a detailed spectral signature for each pixel. This spectral richness allows fine discrimination of vegetation stress, soil properties, and mineral composition, making HSI particularly valuable for precision agriculture, geology, and environmental studies.

A foundational textbook by Richards & Jia (2006) systematically introduced digital image analysis for remote sensing, describing the principles of MSI and HSI. The authors highlighted how MSI offers broader but fewer spectral bands, making it less sensitive to narrowband noise, while HSI provides fine-grained spectral detail but is more vulnerable to atmospheric and sensor-induced noise. Similarly, the pioneering work of Goetz et al. (1985) established the concept of imaging spectrometry and demonstrated its ability to capture subtle spectral variations for material identification. This seminal paper also noted the practical challenge of increased noise susceptibility as spectral resolution increases.

Comparative studies further reinforce these distinctions. Plaza et al. (2009) presented a comprehensive review of hyperspectral image processing, highlighting how HSI’s high dimensionality intensifies challenges such as spectral redundancy, mixed pixels, and noise sensitivity. Their work emphasized that although HSI significantly improves classification capabilities, its effectiveness depends on rigorous preprocessing steps such as denoising and dimensionality reduction. More recently, Roy et al. (2016) compared Sentinel-2 MSI and Landsat-8 MSI for land monitoring, reporting that MSI datasets generally exhibit better noise stability due to their broader spectral channels, though atmospheric corrections remain necessary. Collectively, these studies confirm that MSI is relatively robust against narrowband noise but constrained in spectral discrimination, whereas HSI provides greater spectral detail at the expense of increased sensitivity to noise and redundancy.

This trade-off is summarized in Table 1, which contrasts the noise characteristics and processing requirements of MSI and HSI.

Table 1. Comparative Noise Characteristics and Processing Requirements of MSI and HSI

	Types and Sources of Noise in MSI and HSI	
Aspect	MSI (Multispectral Imaging)	HSI (Hyperspectral Imaging)
Noise stability	MSI datasets generally offer better noise stability due to broader spectral channels, while still requiring atmospheric corrections.	HSI’s high dimensionality amplifies issues of redundancy, mixed pixels, and noise sensitivity
Noise Robustness	MSI is relatively robust against narrowband noise but limited in spectral discrimination	HSI excels in detail but requires careful handling of noise and redundancy.
Coverage vs Sensitivity	MSI provides broad coverage with moderate resilience to noise	while HSI delivers rich spectral information but at the cost of greater noise sensitivity
Filtering / Denoising needs	simpler filtering approaches may suffice for MSI	HSI often requires more advanced machine learning, dimensionality reduction, and spectral–spatial denoising techniques
Impact on Applications	Useful for general remote sensing tasks where moderate noise handling suffices.	while HSI enhances classification capability, preprocessing steps such as denoising and dimensionality reduction are critical for effective use

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III. SOURCES AND TYPES OF NOISE IN PASSIVE REMOTE SENSING

Passive remote sensing data are inherently influenced by multiple noise sources that can degrade image quality and complicate subsequent analysis. Because passive systems depend on reflected solar radiation, noise may arise both from atmospheric interactions (e.g., scattering, absorption, and path radiance) and from sensor-related factors (e.g., calibration errors, thermal noise, and detector instability). Figure 1 illustrates the primary sources of noise in passive remote sensing and Figure 2 . Visualize the sensitivity of both Multispectral imagery and Hyperspectral imagery to noise.

MSI, with its broader spectral bands, generally masks the impact of narrowband noise, offering a more stable but less spectrally detailed representation. In contrast, HSI captures data across hundreds of contiguous narrow bands, which enhances spectral discrimination but also amplifies noise, redundancy, and mixed pixel effects. Consequently, noise reduction and dimensionality reduction become critical preprocessing steps in the HSI processing pipeline. These differences of sensitivity to noise are listed in Table.2.

Furthermore, while MSI can often be corrected using simpler atmospheric and radiometric corrections, HSI typically demands advanced denoising approaches, including spectral–spatial filtering, machine learning-based noise suppression, and feature extraction methods, to fully exploit its high information content. These difference underscores the trade-off between spectral richness and noise resilience in passive remote sensing systems.

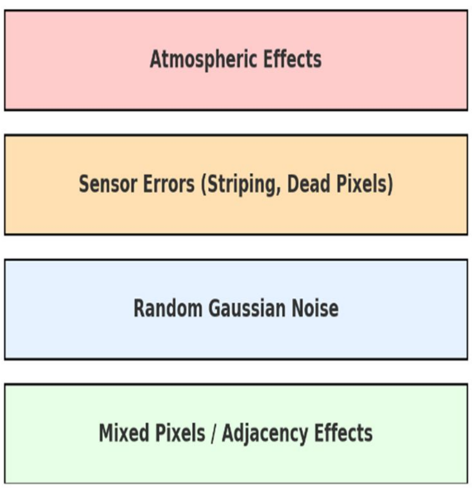

Figure 1: Sources of Noise

Table 2 Behaviour of MSI and HSI towards NOISE

MSI	HSI
with broader bands, tends to mask narrowband noise effects	with hundreds of contiguous channels, amplifies noise and redundancy
MSI is generally more resilient to narrowband distortions due to its broad channels	HSI's fine resolution makes it highly vulnerable to all noise types, necessitating more advanced preprocessing and learning-based denoising approaches.
Typically requires simpler atmospheric and radiometric corrections.	Demands advanced denoising, dimensionality reduction, and spectral–spatial preprocessing to ensure data usability.

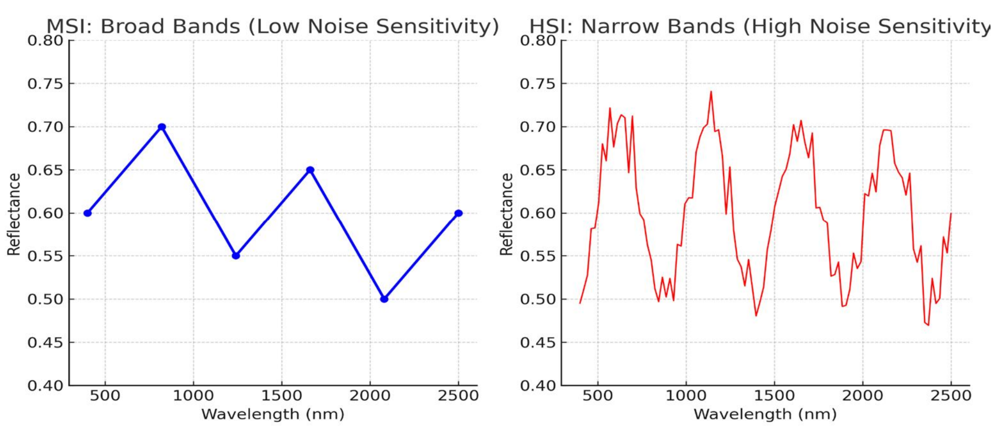

Figure 2. Spectral noise sensitivity in MSI and HSI.

As shown MSI with broad bands (left) demonstrates lower sensitivity to narrowband noise, while HSI with contiguous narrow bands (right) amplifies noise and redundancy, highlighting the trade-off between stability and spectral detail.

The sources of noise in passive remote sensing can be broadly categorized as follows:

1) Atmospheric effects: A major source of noise arises from atmospheric processes, including scattering, absorption, and path radiance variations. These effects distort the spectral signatures of surface materials, often leading to misclassification of land-cover types. Richards & Jia (2006) emphasized that atmospheric correction is indispensable for quantitative remote sensing, while Goetz et al. (1985) noted that the finer spectral resolution of HSI increases its vulnerability to atmospheric noise.
2) Sensor errors: Sensor-induced artifacts such as calibration drift, detector nonuniformity, striping, and dead pixels constitute another important noise source. These issues manifest as systematic band-level or spatial distortions. Plaza et al. (2009) reviewed hyperspectral image processing and demonstrated that striping and Gaussian noise substantially reduce classification performance if left uncorrected. Similarly, Roy et al. (2016) reported that sensor design strongly influences noise resilience, with Sentinel-2 exhibiting reduced striping and radiometric noise compared to Landsat-8.
3) Random noise: Random noise, typically modeled as Gaussian noise, results from electronic fluctuations during data acquisition. In HSI, Gaussian noise affects multiple narrow bands simultaneously, amplifying its impact on spectral unmixing. Zheng et al. (2021) proposed a denoising framework that combines low-rank representation with total variation, effectively mitigating Gaussian and mixed noise in hyperspectral datasets.
4) Mixed pixels and adjacency effects: Due to limited spatial resolution, many pixels represent mixtures of multiple surface materials. This spectral mixing complicates accurate identification of pure endmembers and is especially problematic in HSI, where fine spectral granularity exaggerates redundancy and noise sensitivity. Plaza et al. (2009) identified spectral unmixing as a core challenge intrinsically tied to noise and redundancy.

The relevant satellites and datasets used in passive remote sensing, with their applications and associated noise challenges, are summarized in Table 3.

Table 3 : Passive Remote Sensing Satellites/Datasets (India & Sentinel-2) with Applications and Noise Challenges

Satellite / Sensor	Operator	Key Specifications	Spatial Resolution	Spectral Coverage	Example Applications	Noise Challenges	References
Resourcesat-2 (LISS-III, LISS-IV, AWiFS)	ISRO	Multispectral (4–5 bands)	5.8 m (LISS-IV), 23.5 m (LISS-III), 56 m (AWiFS)	VNIR + SWIR	Agriculture monitoring, land use mapping, crop classification	Striping/banding due to sensor non-uniformity; atmospheric scattering; seasonal haze	Patel et al. (2015); Panigrahy et al. (2010)
Cartosat-2 Series	ISRO	Panchromatic + limited multispectral	0.8–1 m (PAN), 2–5 m (MS)	PAN + VNIR	Urban mapping, infrastructure, high-res land cover	Geometric distortions, adjacency effects in urban areas, sensor-induced random noise	Roy et al. (2016)
HySIS (Hyperspectral Imaging Satellite)	ISRO	Hyperspectral imaging	30 m	55–210 bands (VNIR & SWIR, 0.4–2.4 µm)	Vegetation health, mineral mapping, coastal monitoring	High sensitivity to atmospheric absorption; mixed pixel effects; high dimensional noise redundancy	Chavan & Dhekane (2018)
Sentinel-2 (MSI)	ESA (global, widely used in India)	13 bands (VNIR + SWIR)	10 m (VNIR), 20 m (red-edge/SWIR), 60 m (atmospheric)	VNIR + SWIR (443–2190 nm)	Agriculture, forest monitoring, water quality, atmospheric correction studies	Cloud/haze contamination; adjacency effects; radiometric calibration drift	Roy et al. (2016); Jha et al. (2022)

IV. NOISE REMOVAL TECHNIQUES

Noise in passive RS imagery arises from a variety of sources, including atmospheric scattering, sensor calibration errors, striping, dead pixels, Gaussian disturbances, and mixed-pixel effects. These artifacts reduce classification accuracy, hinder spectral unmixing, and complicate feature extraction pipelines. Plaza et al. (2009) comprehensively reviewed hyperspectral image processing and highlighted denoising, dimensionality reduction, and unmixing as critical preprocessing steps. More recently, Zheng et al. (2021) proposed a low-rank and total variation framework for hyperspectral denoising, demonstrating improved robustness against stripe and Gaussian noise. Despite such advances, many operational studies still treat noise removal as a secondary step rather than a central challenge, leaving a research gap in the development of systematic and comparative reviews focused on noise mitigation

Passive remote sensing imagery, particularly multispectral (MSI) and hyperspectral (HSI) data, is often contaminated by various noise sources such as sensor noise, atmospheric effects, striping, random Gaussian noise, and mixed pixels. Noise not only reduces classification accuracy but also complicates tasks such as feature extraction, spectral unmixing, and dimensionality reduction. To address these challenges, researchers have developed a variety of approaches ranging from statistical filtering to machine learning based denoising.

A. Statistical and Filtering Approaches

Early research primarily relied on smoothing and filtering techniques to suppress high-frequency noise. For instance, Melgani & Bruzzone (2004) demonstrated that Support Vector Machines (SVMs) are inherently robust to noisy, high-dimensional HSI data due to their margin maximization property. Similarly, Ham et al. (2005) showed that Random Forests (RFs) can mitigate noise effects by averaging across multiple decision trees, thereby reducing the impact of outliers.

B. Band Selection and Feature Reduction

Chan & Paelinckx (2008) integrated spectral band selection with ensemble classifiers (RF and AdaBoost), showing that the elimination of noisy or redundant bands enhances ecotope classification accuracy. Dimensionality reduction techniques such as Principal Component Analysis (PCA) and Independent Component Analysis (ICA) have also been widely adopted to reduce noise and redundancy while retaining the most informative spectral features.

C. Ensemble Learning

Briem et al. (2002) highlighted that multiple classifier systems enhance robustness by aggregating decisions from diverse classifiers, effectively reducing sensitivity to noise in individual bands or features. Waske & Benediktsson (2007) further demonstrated that multisensor fusion using SVM ensembles leverages complementary information from radar and optical imagery, thereby compensating for noise present in a single data source.

D. Deep Learning and Representation Learning

Recent studies increasingly employ deep learning (DL)–based denoising strategies. Maxwell et al. (2018) emphasized that DL-driven feature extraction reduces sensitivity to raw noisy inputs by learning stable representations. Pilligundla & Chandre (2025) introduced a transformer-based spectral–spatial optimization architecture that effectively suppresses random noise while enhancing discriminative spectral features. Similarly, Grewal et al. (2023) reviewed spectral–spatial deep networks, noting that the integration of local and contextual information enables significant mitigation of noisy pixel effects.

E. Semi-Supervised and Multimodal Fusion Approaches

Semi-supervised learning has been increasingly adopted to handle the scarcity of clean labeled data. Dhekane et al. (2021) demonstrated that semi-supervised DL methods can leverage large amounts of unlabeled data to learn stable and noise-resilient feature representations, thereby reducing reliance on potentially noisy labeled samples. Rehman et al. (2025) showed that multimodal fusion of HSI with LiDAR improves robustness, as structural information from LiDAR complements and stabilizes noisy spectral measurements.

At the methodological level, much of the remote sensing literature has emphasized classification and feature extraction over noise-specific challenges. Maxwell et al. (2018) reviewed the implementation of machine learning methods in RS, but their emphasis was primarily on applied classification rather than denoising strategies.

Similarly, Grewal et al. (2023) surveyed deep learning techniques for hyperspectral classification, noting how spectral–spatial networks inherently suppress noisy signals by leveraging contextual information. While these works demonstrate the ability of machine learning (ML) and deep learning (DL) methods to handle noisy data indirectly, they underscore the gap that few reviews explicitly position noise removal as the main theme. This limits the availability of consolidated insights for practitioners seeking to adopt robust denoising strategies in operational pipelines.

Classical studies have shown that machine learning models can mitigate noise effects by design. For instance, Melgani and Bruzzone (2004) demonstrated that support vector machines (SVMs) are robust against high-dimensional noisy HSI data due to their margin maximization property. Ham et al. (2005) confirmed that Random Forests reduce noise sensitivity through ensemble averaging, offering improved classification under uncertainty. More recent Indian case studies extend this line of research: Dhekane et al. (2021) proposed semi-supervised deep learning strategies tailored for hyperspectral datasets, effectively leveraging unlabeled data to overcome noise in limited training samples. Likewise, Kambli and Palkar (2024) applied deep learning to crop-specific classification of sugarcane in India, showing how noise handling directly impacts agricultural monitoring accuracy. These works collectively highlight both the progress and the gaps—while various algorithms have been adapted to tolerate noise, a comprehensive review that compares noise removal across MSI and HSI, incorporates Indian case studies, and integrates modern ML/DL advancements is still lacking.

V. APPLICATIONS OF NOISE HANDLING IN INDIAN REMOTE SENSING DATASETS

India's agricultural sector has been one of the primary beneficiaries of passive remote sensing, particularly through the use of multispectral imagery from the Resourcesat series. Patel et al. (2015) employed Resourcesat-2 AWiFS and LISS-III data for crop classification and biophysical parameter retrieval. Their study highlighted how atmospheric and calibration errors influence classification outcomes, with preprocessing methods such as atmospheric correction being essential to ensure data reliability. Similarly, Panigrahy et al. (2010) used multi-temporal Resourcesat-1 AWiFS data for large-scale crop mapping, demonstrating that temporal smoothing effectively reduced random noise and spectral confusion, thereby improving crop discrimination. More recently, Kambli and Palkar (2024) applied deep learning (DL) models for crop-specific classification of sugarcane in India. By incorporating preprocessing techniques such as band normalization, their CNN-based approach achieved higher accuracy than traditional classifiers, illustrating how DL feature extraction can reduce the impact of spectral noise in noisy multispectral imagery. Together, these studies underscore that agricultural monitoring applications in India are particularly sensitive to noise, and both preprocessing and modern ML pipelines play a decisive role in mitigating its effects.

The development of India's Hyperspectral Imaging Satellite (HySIS) has provided an indigenous platform for high-resolution hyperspectral data collection, which brings both opportunities and challenges. Chavan and Dhekane (2018) discussed the potential applications of HySIS in domains such as agriculture, forestry, and geology, while emphasizing that atmospheric correction and calibration are critical to managing noise in such rich datasets. Complementing this, Dhekane et al. (2021) developed semi-supervised deep learning strategies tailored to Indian hyperspectral datasets. Their approach leveraged unlabeled data to stabilize learning under limited and noisy training conditions, significantly improving classification accuracy. These contributions illustrate that while hyperspectral imagery offers finer spectral detail, it is inherently more susceptible to noise, and thus requires advanced learning strategies and robust preprocessing to be fully operational in the Indian context.

Beyond agriculture, passive remote sensing plays a vital role in environmental monitoring and disaster management in India. Jha et al. (2022) utilized Sentinel-2 multispectral data to monitor forest fire damage, addressing the challenges posed by smoke and haze. Their study showed that atmospheric correction and spectral filtering were essential to reliably detect fire-affected regions, with classification accuracy maintained even under severe spectral noise. Similarly, Roy et al. (2016) conducted a comparative evaluation of Sentinel-2 and Landsat-8 data, analyzing radiometric performance and noise characteristics. Their results demonstrated that Sentinel-2 had lower striping and better radiometric quality, making it more suitable for noise-sensitive applications such as vegetation and land cover monitoring in India. These findings emphasize that sensor selection and preprocessing choices directly influence the robustness of noise handling in environmental studies.

VI. FUTURE DIRECTIONS

Noise removal in passive remote sensing has evolved considerably, yet several critical opportunities remain for advancing both algorithms and sensor technology. Current approaches focus largely on post-acquisition preprocessing and machine learning–based denoising pipelines, but there is increasing potential for direct integration of noise mitigation within the sensors themselves.

One promising direction is the development of onboard noise-aware sensors, where denoising algorithms or adaptive calibration routines are embedded at the hardware or firmware level. For example, real-time striping correction, detector non-uniformity adjustments, and atmospheric compensation modules could be directly integrated into MSI and HSI platforms during image acquisition. Such in-sensor processing would reduce the propagation of noise into downstream analysis and minimize reliance on extensive post-processing. This paradigm shift towards "smart sensors" aligns with broader trends in edge computing and autonomous satellites, where data are pre-processed before transmission to ground stations.

A second emerging direction is physics-informed deep learning that merges radiative transfer models with neural architectures. By embedding physical priors into denoising networks, these methods can ensure spectral fidelity while still leveraging the robustness of ML/DL. This is particularly relevant for hyperspectral data, where maintaining the physical interpretability of narrow bands is essential.

Another future trend is the fusion of multimodal sensing (HSI–LiDAR, MSI–SAR, or HSI–thermal) implemented directly at the sensor constellation or onboard processing unit. Such multimodal frameworks can exploit complementary information in real-time, reducing spectral noise sensitivity and improving scene understanding.

Additionally, semi-supervised and self-supervised pretraining strategies hold potential for improving denoising without requiring large, clean, labeled datasets. Combined with transformer-based architectures, these methods can learn spectral–spatial correlations more efficiently and adapt to domain shifts across regions and sensors.

Finally, there is a pressing need for benchmark datasets and open pipelines tailored to Indian scenarios. Standardized datasets from Resourcesat, Cartosat, HySIS, and Sentinel-2 with annotated noise levels would accelerate reproducibility and algorithm development. Coupling such benchmarks with cloud-native platforms would make noise-resilient pipelines more accessible to practitioners.

VII. CONCLUSION

This review synthesized developments in noise removal for passive remote sensing, highlighting sources of noise, comparative impacts on MSI and HSI, and the evolution of mitigation strategies from classical filtering to deep learning and multimodal fusion. A comparative perspective demonstrated that MSI, with fewer broad bands, is less sensitive to narrowband distortions and benefits primarily from preprocessing and robust classifiers, while HSI, with hundreds of contiguous channels, demands advanced ML/DL approaches to suppress amplified noise and redundancy.

Indian case studies using Resourcesat, Cartosat, HySIS, and Sentinel-2 underscored that noise removal is not a peripheral step but a central requirement for reliable agricultural monitoring, environmental assessment, and disaster management. These studies illustrate how atmospheric corrections, semi-supervised learning, and deep models have improved resilience to noise in real-world applications.

Looking forward, future research must move beyond algorithmic denoising to sensor-level innovations, including noise-aware detectors and in-sensor calibration routines that enhance data quality at acquisition. Coupled with physics-informed deep learning and multimodal fusion, such approaches will create noise-resilient pipelines that are both efficient and physically reliable. By combining algorithmic advances with sensor hardware integration and benchmark development, the remote sensing community can move toward robust, reproducible, and operationally impactful noise mitigation, particularly in the Indian context where open satellite data and applications are rapidly expanding.

In this context, the contribution of this review is threefold: (i) to systematically survey noise sources and mitigation strategies in passive RS, spanning statistical filtering, band selection, ensemble learning, and advanced ML/DL methods; (ii) to provide a comparative perspective on how noise impacts MSI and HSI differently, drawing insights from both classical and modern approaches; and (iii) to ground the discussion in the Indian context by highlighting case studies that employ open datasets such as Resourcesat, Cartosat, HySIS, and Sentinel-2. By addressing these research gaps, the paper seeks to consolidate fragmented knowledge on noise handling, highlight emerging trends such as transformer-based architectures and multimodal fusion, and outline future directions for building noise-resilient remote sensing pipelines.

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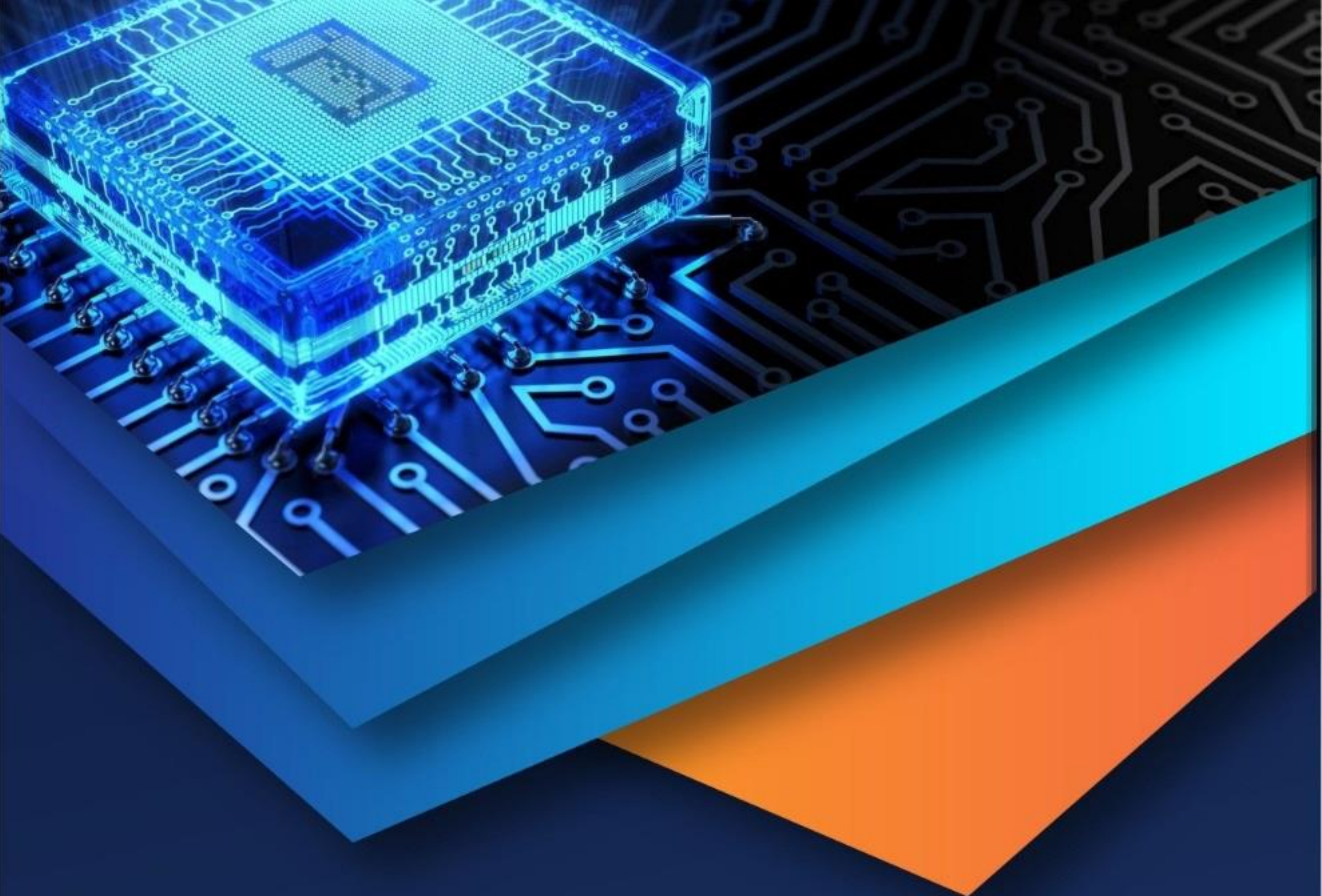

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