remote sensing

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Review

Evaluating Protected Area Effectiveness: A Remote Sensing Review

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Highlights

What are the main findings?

- A dual-dimensional framework integrating management effectiveness and conservation effectiveness is proposed to address the fragmentation of existing Remote Sensing (RS)-based Protected Area (PA) assessment syntheses.
- Existing RS assessments reveal that 33% of global protected land remains under intense pressure; greenness-based metrics may overestimate conservation success by masking underlying resilience declines.

What are the implications of the main findings?

- With just 18.29% of the area within global PAs having undergone management effectiveness assessments, scaling up RS-enabled evaluation through tiered, biome-adaptive indicator systems is critical to close this vast assessment gap.
- Embedding RS into routine PA governance via AI-driven multi-source fusion, transboundary species monitoring, and ecosystem service valuation can operationalize the "30 × 30" target.

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Abstract

Protected Areas (PAs) are essential for global biodiversity conservation, yet assessing their management and conservation effectiveness remains a formidable challenge. While remote sensing (RS) enables synoptic, large-scale monitoring, existing reviews are often fragmented—either decoupled from PA governance contexts or confined to isolated threat mappings. To bridge this gap, this review proposes a dual-dimensional analytical framework integrating management effectiveness and conservation effectiveness. Based on the literature retrieved via a systematic Boolean search in the Web of Science, we first establish a multi-source RS technology stack covering space-borne optical, radar, nighttime-light, LiDAR and

cloud-computing platforms. We then review RS applications within the two dimensions. For management effectiveness, we trace the progression from single-disturbance tracking to integrated pressure assessments using counterfactual matching designs. For conservation effectiveness, we synthesize advances in biodiversity dynamics, ecosystem pattern integrity, quality evaluation, and ecosystem service quantification. Our review demonstrates that RS has become a major component of large-scale PA evaluation, revealing measurable successes while highlighting the risk of overestimating conservation outcomes when relying solely on greenness-based proxies. Persistent challenges include the lack of standardized, biome-specific assessment frameworks and the disconnect between biophysical monitoring and socio-ecological drivers. Addressing these gaps requires unified evaluation systems aligned with the Kunming-Montreal Global Biodiversity Framework, AI-driven multi-sensor fusion, and the operationalization of RS into routine PA governance to support the "30 × 30" target and ecological product value realization.

Keywords: remote sensing; protected areas; management effectiveness; conservation effectiveness; Global Biodiversity Framework; human pressure; ecological integrity; counterfactual matching

1. Introduction

Protected Areas (PAs) constitute the cornerstone of global biodiversity conservation, serving as the primary defense against accelerating species loss and ecosystem degradation [1]. They are instrumental in advancing United Nations Sustainable Development Goal 15 (Life on Land) [2] and the strategic objectives of the Convention on Biological Diversity. As of 2024, the global PA network has expanded to cover 17.6% of terrestrial and inland water areas and 8.4% of marine and coastal areas [3]. Under the newly adopted Kunming-Montreal Global Biodiversity Framework (GBF), the world has committed to the ambitious "30 × 30" target, aiming to place 30% of terrestrial and marine areas under protection by 2030 [4]. While this extensive network signifies a substantial investment of financial resources and entails significant opportunity costs associated with foregone land use [5], it also raises a pressing question for the scientific community and policymakers: Are these massive investments effectively conserving biodiversity and delivering expected ecological outcomes—both by mitigating anthropogenic pressures through on-ground management inputs, and by maintaining or restoring ecological integrity, habitat quality, and ecosystem service provision?

The evaluation of PA management and conservation effectiveness is thus a topic of widespread concern [6–10]. However, conducting such evaluations presents formidable challenges. The vast diversity in PA types, coupled with their immense spatial scale and the increasing impacts of global climate change [11], complicates the assessment process. This complexity is particularly pronounced in large and developing countries, where traditional field-based monitoring methods—reliant on ground surveys—prove inadequate [12]. These conventional approaches are often constrained by limited spatial coverage, high costs, and poor temporal resolution. The Protected Planet Report 2020 highlighted this assessment gap, revealing that only 18.29% of the area within PAs globally has undergone management effectiveness assessments [13].

In contrast, Earth observation technologies offer distinct advantages for overcoming these limitations [14,15]. A bibliometric analysis of 4546 related publications reveals a consistent upward trend in annual outputs concerning remote sensing (RS) applications in PAs, signaling the field's rapid maturation [16]. This trajectory is mirrored in specific research streams; for instance, a recent review of 51 spillover analyses published between

2000 and 2024 found that 39 studies employed satellite RS as their primary data source [17], underscoring the extent to which the field has embraced RS as its dominant data source. RS provides synoptic, repetitive, and cost-effective observations across multiple spatiotemporal scales, enabling the quantification of spillover effects over territories that are logistically impossible to survey on the ground. The proliferation of multi-source, multi-temporal satellite data has allowed researchers to apply RS-based methodologies to PA assessment at unprecedented breadth, significantly enhancing both the efficiency and spatial coverage of evaluation [18]. This technological shift has facilitated the rapid evaluation of conservation management and outcomes, scaling from individual reserves to continental and even global levels [19,20].

Despite the proliferation of RS applications in ecology, a synthesis specifically bridging RS technologies with PA management and conservation effectiveness remains insufficient. Yet existing reviews exhibit a fragmented focus. Ecological monitoring syntheses—such as Reddy [21] and Wang and Gamon [22]—primarily examine how RS quantifies biodiversity patterns or proxies, but largely remain decoupled from the specific governance contexts of PAs. Conversely, threat-mapping syntheses—exemplified by Luo, Li, Wang and Cheng [18], who systematically reviewed seven major types of anthropogenic pressure and four key mapping methodologies—concentrate on detecting disturbances yet fail to link these pressures back to an overarching evaluation framework for PA performance. This fragmentation persists despite repeated calls for a "step change" in PA effectiveness through increased recognition, funding, planning, and enforcement [1]. As Gohr, von Wehrden, May and Ibisch [14] demonstrated through a qualitative and quantitative analysis of 44 peer-reviewed papers, current remotely sensed effectiveness assessments lack a common framework, with most studies confined to local-scale case studies and single indicators such as forest cover change [17,23]. This disconnect limits the ability of scholars and policymakers to leverage big data and artificial intelligence for targeted interventions. Without a unified framework, the potential of RS to address the nuanced challenges of PA governance remains underutilized. To bridge these gaps, this review moves beyond isolated case studies by structuring the synthesis around a two-dimensional evaluation framework. The first dimension—management effectiveness—adopts a process-oriented approach centered on detecting anthropogenic threats. Complementing this, the second dimension—conservation effectiveness—provides an outcome-oriented assessment focused on biodiversity responses and ecological outcomes.

Following this structure, we first synthesize the multi-source RS technology stack for PA monitoring, covering spaceborne optical, radar and nighttime-light sensors, spaceborne LiDAR, and cloud-computing platforms that underpin large-scale assessments. We then review state-of-the-art RS applications within the two dimensions. For management effectiveness, we summarize progress in both single-disturbance tracking and integrated pressure evaluation. For conservation effectiveness, we synthesize advances in biodiversity monitoring, ecosystem pattern assessment, ecosystem quality evaluation, and ecosystem service quantification. Finally, we critically identify persistent operational challenges and outline corresponding future directions to address them. By establishing this structured roadmap, this review aims to clarify the current state of RS applications in PA effectiveness evaluation, foster synergies between technological innovation and conservation practice, and provide a reference for aligning assessment frameworks with the strategic goals of the Kunming-Montreal GBF.

2. Review Scope and Analytical Framework

2.1. Search Strategy and Study Selection

This review adopts a targeted synthesis rather than a full systematic review. To ensure transparency and reproducibility while preserving conceptual coherence with protected-area (PA) governance, the literature selection was guided by an explicit search strategy, inclusion/exclusion criteria, and a dual-dimensional analytical framework that links RS technologies to management effectiveness and conservation effectiveness.

A systematic literature search was conducted in the Web of Science Core Collection database, covering all publications from 1975 to the last search date of 1 October 2026. The query was structured around four conceptual blocks: (i) RS technology; (ii) PA items; (iii) management effectiveness; and (iv) conservation effectiveness. The four blocks were defined as follows.

Block A (RS technology): (remote sensing OR remotely sensed OR satellite* OR "Earth observation" OR SAR OR LiDAR OR "nighttime light*" OR "Google Earth Engine" OR GEE OR MODIS OR Landsat).

Block B (PA items): ("protected area*" OR "national park*" OR "nature reserve*" OR "biosphere reserve*" OR "marine protected area*" OR "IUCN categor*" OR "wilderness area*").

Block C (Management effectiveness): ("management effectiveness" OR "human pressure" OR "human footprint" OR "human modification" OR "anthropogenic disturbance*" OR "urban*" OR "cropland expansion" OR mining OR "road*" OR "nighttime light*" OR "light pollution" OR wildfire OR logging OR deforestation).

Block D (Conservation effectiveness): ("conservation effectiveness" OR "ecological outcomes" OR biodiversity OR "ecosystem service*" OR "ecosystem quality" OR "landscape pattern*" OR NDVI OR NPP OR "canopy height" OR GEP OR resilience).

Four complementary Boolean search strings were executed to partition the retrieved literature into distinct evaluation subsets. The first string, A AND B AND (C OR D), retrieved all RS-based PA effectiveness studies spanning either management or conservation dimensions, representing the full retrieved set. The second string, A AND B AND C AND D, identified studies addressing both dimensions simultaneously. The third string, A AND B AND C, isolated studies focused on management effectiveness. The fourth string, A AND B AND D, captured studies dedicated to conservation effectiveness. Together, these four subsets enabled both comprehensive bibliometric profiling and a stratified synthesis across evaluation dimensions.

Records retrieved were merged and deduplicated by title and DOI. First, titles and abstracts were screened against the review scope: a record was retained if it (i) used RS or Earth-observation data; (ii) evaluated or exemplified applications in PAs, including terrestrial, freshwater, or marine PAs; and (iii) addressed either management effectiveness (anthropogenic pressure, disturbance, or management input) or conservation effectiveness (biodiversity, ecosystem pattern, quality, or services). Records were excluded if they focused only on sensor algorithm development without PA application, discussed PAs without RS data, or addressed non-PA conservation contexts unrelated to the dual-dimensional framework. Full texts of potentially eligible records were then assessed, and additional studies were added by backward/forward citation tracking of key global assessments to reduce coverage bias.

Because the review is a targeted synthesis rather than an exhaustive systematic map, studies were not selected solely by frequency of appearance. Instead, priority was given to publications that (i) represent global, continental, or multi-PA assessments; (ii) illustrate single-disturbance or integrated-pressure methods for management effectiveness; (iii) illustrate biodiversity, landscape pattern, ecosystem quality, or ecosystem-service methods for conservation effectiveness; and (iv) improve geographic, biome, and IUCN-category balance.

2.2. Analytical Framework

The retained literature was organized along the sequential workflow of PA governance. Section 3 synthesizes the RS technology stack—optical, radar and nighttime-light, spaceborne LiDAR, and cloud-computing platforms. Sections 4 and 5 then translate these technical capacities into the two core dimensions of effectiveness: Section 4 focuses on management effectiveness, detailing how RS quantifies anthropogenic disturbance dynamics, and Section 5 shifts to conservation effectiveness, examining how RS captures ecological responses including biodiversity trends, landscape pattern integrity, and ecosystem service provision. Section 6 critiques persistent challenges and outlines future directions aligned with the Kunming-Montreal GBF and the "30 × 30" target.

The dual-dimensional logic is visualized in Figure 1. The search strategy does not claim that every retrieved record was included; rather, it provides a transparent, reproducible evidence base from which representative studies were selected to support the narrative synthesis.

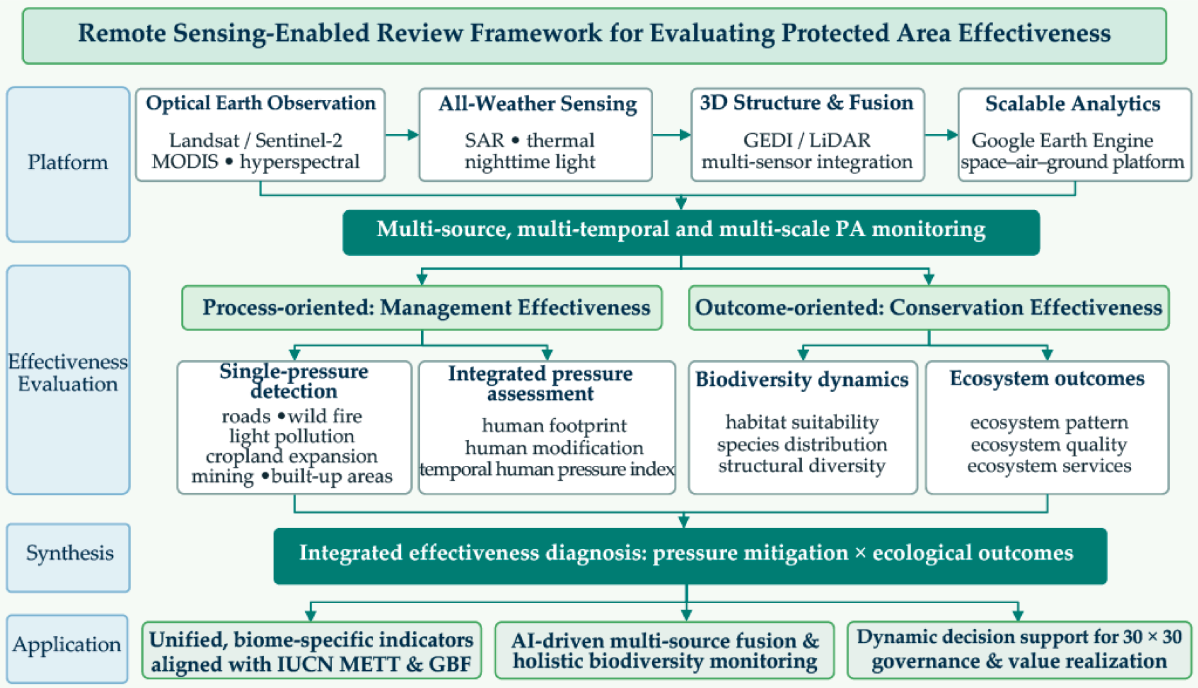


Figure 1. The dual-dimensional analytical framework proposed in this review, linking remote sensing (RS) technologies to protected area (PA) effectiveness evaluation.

2.3. Descriptive Profile of the Retrieved Literature

A total of 5864 publications were retrieved from the Web of Science Core Collection. Among these, 3101 publications focused specifically on management effectiveness, while 4338 publications focused on conservation effectiveness. Notably, 1575 publications—approximately 26.9% of the total corpus—simultaneously engaged with both dimensions.

To provide an overview of the geographic representation of the retrieved literature, authorship countries/regions were extracted from the Web of Science Core records. Figure 2 shows the spatial distribution of publication counts across 165 recorded regions. The output of publications is extremely concentrated. The top five contributing countries—the United States, China, Germany, the United Kingdom, and Australia—collectively account for 47.3% of the total volume, while the top ten countries contribute 61.0%, reflecting the concentration of RS and conservation research capacity in these regions.

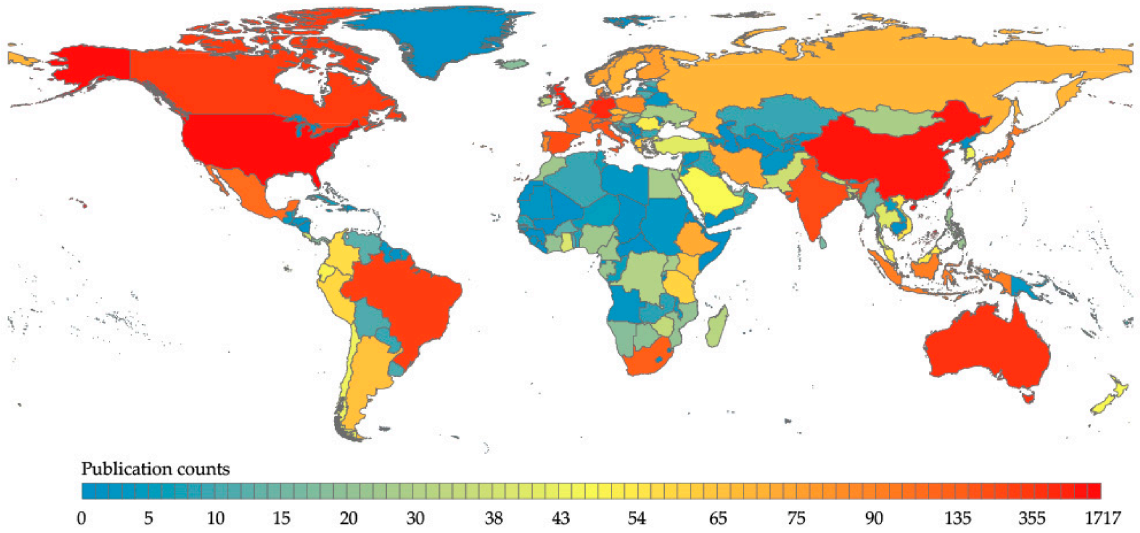


Figure 2. Global geographic distribution of publication counts on RS applications in PAs by country/region.

Figure 3 illustrates the annual publication trend from 1990 to 2026. Publications in this field remained sparse before 2000, began to increase notably around 2005–2008, and have grown rapidly since 2010, with over 70% of the retrieved records published after 2015. The trajectory peaked around 2025, reflecting the maturation of RS as the data source for PA effectiveness evaluation and its alignment with the Kunming-Montreal GBF monitoring agenda.

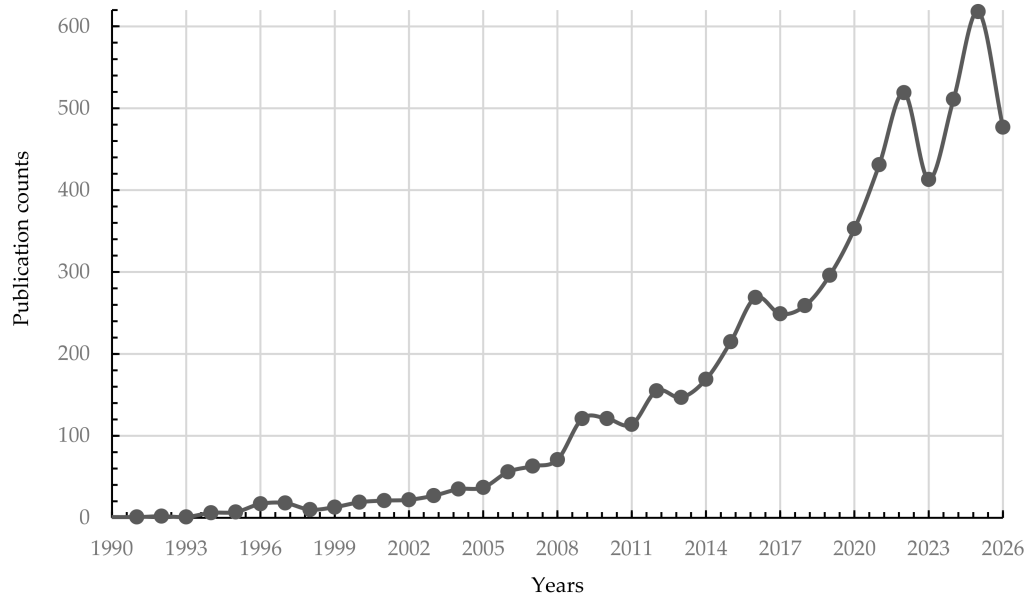


Figure 3. Annual publication trend of the retrieved literature on RS applications in PAs from 1990 to 2026.

3. RS Technology Stack for PA Monitoring

The evolution of RS technologies has fundamentally transformed humanity's capacity to monitor PA at unprecedented spatial and temporal scales. To establish the technological foundation for subsequent discussions on management and conservation effectiveness, this section synthesizes the multi-tiered "space–air–ground (i.e., satellite, aerial/UAV, and ground-based monitoring)" RS platform ecosystem that underpins modern PA assessments. Bibliometric analyses confirm the central role of specific sensors in this endeavor: among

4546 publications on PA RS from 1991 to 2018, Landsat, MODIS, and LiDAR rank as the most frequently used satellite and sensor platforms, with research hotspots concentrated on change detection, biodiversity conservation, and climate change impacts [16]. Building on this quantitative baseline, the following sections detail the four principal technological pillars—optical imagery, radar and nighttime-light sensing, spaceborne LiDAR, and cloud-computing-integrated platforms—each illustrated with global to continental scales benchmark applications (Table 1).

Table 1. Overview of RS platforms for PA effectiveness evaluation.

Sensor Type	Representative Platform	Applications in PA Monitoring	Representative Large-Scale Studies
Optical	Landsat 5/7/8/9 (30 m), Sentinel-2 (10–60 m), MODIS (250–500 m)	Land-cover change, vegetation indices, habitat integrity	Li et al. [24] and Ren et al. [25]: global mining-induced habitat loss in PAs
Radar (SAR)	Sentinel-1 (5–20 m), ALOS-2 PALSAR-2 (3–10 m)	Forest structural change in cloud-prone regions, deforestation	Doblas et al. [26] and Kilbride et al. [27]
Nighttime Light (NTL)	DMSP/OLS (30 arc-sec), VIIRS/DNB (15 arc-sec)	Artificial light pollution monitoring, urbanization pressure	Mu et al. [28] and Fan et al. [29]: global light pollution assessment in PAs
Spaceborne LiDAR	GEDI (25-m footprint)	Canopy height, vertical structure, biomass estimation, habitat complexity	Ceccherini et al. [30]: European forest structure comparison in PAs
Cloud Computing	Google Earth Engine, Amazon Web Services, OpenEO	Multi-sensor data fusion, reproducible global assessments	Enabled [24,25,28]

3.1. Spaceborne Optical Imagery

Optical sensors remain the primary source of data for PA monitoring, providing the multi-decadal, globally consistent archives necessary for detecting land-cover change and evaluating conservation outcomes [31]. The Landsat series and its successor Sentinel-2 deliver 30 m and 10–20 m resolution multispectral observations, respectively, enabling wall-to-wall change detection within PAs from local to global scales. MODIS complements these with daily global coverage at coarser resolutions (250–500 m), supporting continuous vegetation indices and phenology metrics essential for ecosystem quality assessment.

The unparalleled temporal depth of the Landsat archive has enabled unprecedented global-scale assessments of PA effectiveness. Li, Fang, Watson, Sun, Qi, Wang and Liu [24] leveraged global 30-m resolution land use data—fundamentally derived from multi-temporal optical satellite observations—to evaluate habitat loss resistance across over 160,000 PAs from 2003 to 2019 using counterfactual matching. This study exemplifies how the continuity of optical satellite records underpins evaluations of conservation outcomes at planetary scales. At finer spatial scales, high-resolution optical imagery has exposed previously overlooked anthropogenic threats. Ren, Hu, He, Zhao, Lu, Li, Zhang, Zhang, Cao, Yang, Wu, Sun, Wang and Chen [25] presented a global assessment of mining-induced forest loss within and beyond PAs from 2001 to 2020, finding that ~11% of global mining-induced forest loss occurs within PAs, rising to ~19% during 2016–2020. This study illustrates how multi-temporal optical change detection can uncover cryptic, trans-boundary anthropogenic pressures that threaten PA integrity. Together, these two global assessments—spanning habi-

tat loss and mining encroachment—demonstrate that optical RS serves as the indispensable component for both management and conservation effectiveness evaluation.

3.2. Radar and Thermal/NTL Sensing

While optical sensors face inherent limitations under cloud cover and fail to detect non-structural anthropogenic disturbances, radar and NTL RS provide critical complementary capabilities. Synthetic Aperture Radar (SAR), operating independently of solar illumination and atmospheric conditions, enables all-weather, day-and-night monitoring of forest structural change—particularly valuable in tropical and monsoon regions where persistent cloud cover hinders optical observation. A pioneering operationalization of this capability is the prototype SAR-based forest alert system of Kilbride, Poortinga, Bhandari, Thwal, Quyen, Silverman, Tenneson, Bell, Gregory, Kennedy and Saah [27], who achieved near-real-time forest disturbance detection over two Cambodian wildlife sanctuaries using Sentinel-1 C-band radar data, effectively overcoming the persistent monsoon cloud cover that limits optical monitoring. Thermal infrared sensors further support wildfire detection, evapotranspiration estimation, and heat island assessments within PAs. NTL RS occupies a unique niche: it exposes anthropogenic pressures imperceptible to conventional optical change detection. The significance of this capability is underscored by the fact that artificial light pollution alters natural light–dark patterns in PAs, posing a global threat to biodiversity. Fan, Zhao, Wang, Ren, Zhang and Guo [29] conducted a global assessment of NTL for terrestrial PAs and wilderness areas, demonstrating that artificial light penetrates PA boundaries and compromises wilderness character—a stressor undetectable via standard optical methods.

The analytical power of NTL for PA monitoring was comprehensively demonstrated by Mu, Li, Du, Huang, Su, Hu, Wen, Yin, Han and Xue [28], who developed a novel framework to evaluate light pollution status across 30,624 global PAs from 1992 to 2018, using a harmonized global NTL time-series dataset. Their study classified all PAs into three categories: non-polluted, continuously polluted, and discontinuously polluted. The methodological foundation of this assessment rests on the harmonized DMSP-VIIRS NTL dataset (1992–2018) produced by Li et al. [32], which reconciled severe inconsistencies between the DMSP/OLS (1992–2013) and VIIRS/DNB (2012–2018) sensors through a sigmoid function conversion, generating a consistent 27-year global NTL archive at 30-arc-second resolution. This integration of Fan et al.'s [29] conceptual demonstration with Mu et al.'s [28] global operationalization exemplifies how NTL RS provides an irreplaceable lens on "non-green" anthropogenic disturbances, directly informing the management effectiveness dimension of PA evaluation.

3.3. Spaceborne LiDAR and Multi-Sensor Fusion

Conventional optical imagery yields primarily two-dimensional information, which is insufficient for characterizing forest 3D structure. Spaceborne LiDAR systems, such as NASA's Global Ecosystem Dynamics Investigation (GEDI) and ICESat-2, provide direct measurements of canopy height and vertical structure. These metrics are core indicators of ecological integrity, particularly for carbon stock accounting.

Ceccherini, Girardello, Beck, Migliavacca, Duveiller, Dubois, Avitabile, Battistella, Barredo and Cescatti [30] harnessed the power of this technology by analyzing over 30 million GEDI records to compare forest vertical structure indicators inside and outside nearly 10,000 PAs across Europe. Their findings revealed that European forests within PAs are on average 2 m taller and vertically more complex than those in nearby unprotected areas, while forests outside PAs exhibit greater canopy height variation—likely reflecting past and ongoing forest management operations. This continental-scale assessment demonstrates

that spaceborne LiDAR enables the large-scale monitoring of forest vertical structural attributes that are key to conservation and restoration policy, filling a critical gap left by 2D optical sensors.

Recognizing the spatially discrete sampling limitation of GEDI footprints, recent advances have coupled LiDAR with optical sensors' temporal continuity. This fusion paradigm—combining LiDAR's 3D structural sensitivity with optical sensors' global coverage—represents the frontier of PA ecological integrity assessment. Potapov et al. [33] integrated GEDI-derived canopy height with multi-temporal Landsat metrics to produce a global 30-m resolution forest canopy height map, enabling multidecadal annual monitoring of forest structural dynamics. Such multi-sensor fusion directly supports the biodiversity and ecosystem quality dimensions of conservation effectiveness evaluation, providing the empirical foundation for assessing whether PAs genuinely preserve ecological integrity rather than merely preventing land-cover conversion.

3.4. Cloud Computing and the "Space–Air–Ground" Integrated Platform

The convergence of multi-source RS data and computational platforms has fundamentally transformed PA monitoring workflows. As bibliometric trends indicate, PA RS publications exhibited sustained growth from 1991 to 2018 [16], reflecting both sensor proliferation and algorithmic advancement. Cloud-based platforms such as Google Earth Engine (GEE) now enable the processing of petabyte-scale Landsat, Sentinel, MODIS, and GEDI archives through parallelized computing, eliminating the traditional bottleneck of downloading and preprocessing massive data volumes. This computational leap has been instrumental in enabling the global-scale assessments described in Sections 3.1–3.3: Li, Fang, Watson, Sun, Qi, Wang and Liu [24] processed 160,000+ PAs; Ren, Hu, He, Zhao, Lu, Li, Zhang, Zhang, Cao, Yang, Wu, Sun, Wang and Chen [25] assessed mining impacts across global PAs; and Mu, Li, Du, Huang, Su, Hu, Wen, Yin, Han and Xue [28] evaluated light pollution across 30,624 PAs—all made computationally feasible by GEE and similar platforms.

Beyond pure spaceborne observation, the "space–air–ground" integrated architecture establishes a hierarchical monitoring system: geostationary and polar-orbiting satellites provide macro-scale screening; airborne and UAV platforms fill spatial–temporal gaps and verify anomalies at fine resolution; and ground-based sensor networks, including camera traps, acoustic monitors, eDNA samplers, and IoT weather stations, deliver direct ecological validation. This integrated paradigm bridges the gap between remote proxies and on-ground ecological reality, addressing the "wall of complexity" that separates RS observations from direct biodiversity measurement. The technological foundation laid out in this section—from optical archives through LiDAR fusion to cloud-integrated platforms—provides the essential toolkit for the management and conservation effectiveness evaluations detailed in Sections 4 and 5, while simultaneously framing the operational barriers and future priorities discussed in Section 6.

4. RS for Management Effectiveness of PA

The ecological health of PAs is fundamentally determined by whether internal anthropogenic disturbances are effectively managed and controlled. This logic sits at the very core of the IUCN PA classification system—from Ia (Strict Nature Reserve) to VI (PA with Sustainable Use of Natural Resources), the essential distinction lies precisely in what types and intensities of human activities are permitted. Consequently, the primary application of RS in evaluating PA management effectiveness is the monitoring of internal human disturbances and the tracking of their dynamics, which achieves efficiencies orders of magnitude higher than traditional ground-based surveys. Research scales span from a single PA to multiple

PAs within a region, and even to continental- and global-scale assessments encompassing tens of thousands of PAs. Considerable progress has been made. Generally speaking, RS technologies have been employed for both the monitoring of individual and integrated human disturbance within PAs.

4.1. RS Monitoring of Individual Human Disturbances Within PAs

Early applications of RS for PA management effectiveness evaluation predominantly focused on the monitoring and change detection of individual disturbance types. Within this framework, researchers have systematically monitored cropland expansion, residential sprawl, transportation infrastructure, tourism facilities, industrial and mining development, NTL, and other discrete human-induced alterations to the land surface, using multi-temporal optical satellite imagery and NTL data as primary sources.

Among single-disturbance monitoring efforts, cropland expansion has attracted substantial global attention because of its direct threat to the post-2020 GBF (Table 2). Meng et al. [34] used 30-m spatial resolution global cropland data layers to characterize cropland dynamics across global PAs from 2000 to 2019. The study revealed that cropland expansion within PAs accelerated dramatically compared to the expansion of global croplands, with areal expansion concentrated primarily in large PAs, less-strict PAs, and Afrotropical PAs—regions that coincide with higher species extinction risks. Notably, even some PAs with the highest conservation levels failed to prevent cropland encroachment, indicating that agricultural pressure poses an ongoing, intractable global conservation challenge.

Table 2. Representative global scale studies on RS monitoring of individual anthropogenic disturbances within PA.

Disturbance Type	Spatial Scale	Data Source(s)	Methods	Key Findings	References
Cropland expansion	Global PAs, 2000–2019	30-m global cropland maps	Annual cropland change detection; overlay with species extinction risk maps	Cropland expansion in PAs accelerated faster than global croplands	Meng, Dong, Ellis, Metternicht, Qin, Song, Löfqvist, Garrett, Jia and Xiao [34]
NTL (light pollution)	Global PAs, 1992–2018	DMSP/OLS; harmonized DMSP-VIIRS	0–100 km IUCN PA buffer gradient analysis; temporal classification into non-/continuous/discontinuous pollution	6.9% of PAs affected; buffer zones > interior; 26.5% continuously polluted	Fan, Zhao, Wang, Ren, Zhang and Guo [29]; Mu, Li, Du, Huang, Su, Hu, Wen, Yin, Han and Xue [28]
Mining-induced Forest loss	Global (Inside & 1–10 km outside PAs)	Global mining land use data, global forest change	Spatiotemporal analysis of forest loss linked to active mining	11% of global mining-related forest loss occurred inside PAs; this rose to 19% post-2016	Ren, Hu, He, Zhao, Lu, Li, Zhang, Zhang, Cao, Yang, Wu, Sun, Wang and Chen [25]
Built-up area expansion	Global PAs & 10-km buffers, 1975–2014	Global built-up area dataset	Comparative analysis of built-up coverage trends (PA interior vs. buffer zones)	Built-up coverage reached 0.1% within PAs vs. 2.7% in 10-km buffers in 2014	Fuente et al. [35]
Road/railway-induced forest loss	Global; 1-km grids; 2000–2020	OpenStreetMap + GRIP4 road datasets; forest cover	Grid-based background matching; road impacts as absolute/normalized disparities; distance-decay analysis	Within 1 km: −18.6% cover, −2.7 m height, −52.2 NPP, +23.0 fragmentation; impacts decay to 5 km	Zhou et al. [36]
Wildfire disturbance	Global PAs, 2001–2024	Satellite-derived fire occurrence and burn area data	Comparative analysis of burned area; biome-stratified assessment	PAs occupy 19.2% of semi-natural ecosystems but account for 28.5% of annual global burn area	Resco de Dios et al. [37]

NTL and light pollution constitute another prominent strand of single-disturbance monitoring. Fan, Zhao, Wang, Ren, Zhang and Guo [29] used DMSP/OLS nighttime stable light data from 1992 to 2013 to assess night-time lighting across global terrestrial PAs and wilderness areas, stratified by the seven IUCN management categories. They found that globally 6.9% of PAs are affected by NTL, with Type V PAs exhibiting the highest NTL levels and Type Ib the lowest. Extending this line of inquiry, Mu, Li, Du, Huang, Su, Hu, Wen, Yin, Han and Xue [28] developed a comprehensive framework using global NTL time-series data from 1992 to 2018 [32]. Their analysis demonstrated that global light pollution is mainly distributed between 30°N and 60°N, covering Europe, North America, and East Asia, and that although the temporal trend of NTL intensity in global PAs is increasing overall, Japan and the United States exhibit opposite trends attributable to well-planned ecological conservation policies and declining population growth.

Industrial mining has emerged as a rapidly intensifying yet often underestimated driver of forest loss within and around PAs [38]. Ren, Hu, He, Zhao, Lu, Li, Zhang, Zhang, Cao, Yang, Wu, Sun, Wang and Chen [25] addressed this gap through a global spatiotemporal analysis linking 2001–2020 forest loss to active mining sites using harmonized global mining land-use and forest change datasets. Their findings reveal a concerning trend: approximately 11% of global mining-related forest loss occurred inside PAs, a figure that surged to 19% in the period following 2016 amid accelerating demand for critical minerals. Crucially, mining-induced forest loss exhibits significant spatial leakage beyond PA borders, with losses in the 1–10 km buffer zone reaching three times the magnitude of internal PA loss.

Beyond extractive industries, built-up area expansion represents another pervasive yet spatially differentiated pressure on PAs. A global assessment of all PAs larger than 5 km^2 reveals that while built-up areas covered only 0.12% of PA extent in 2014, the adjacent 10-km unprotected buffers exhibited a markedly higher 2.71% coverage [35]. Critically, built-up area growth in the buffers was 23 times larger than inside PAs from 1975 to 2014, with Europe and Asia bearing the highest pressure and coastal/small PAs being disproportionately affected (Table 2).

Beyond transportation infrastructure, road/railway-induced forest degradation and loss represents another pervasive yet spatially differentiated pressure on PAs. Zhou, Xiao, Liu, Huang, Zhang, Fan and Zhao [36] addressed this gap through a global analysis quantifying road impact on forest metrics (2000–2020) using OpenStreetMap and GRIP4 road datasets. Their findings reveal a concerning trend: within 1 km of roads, forest cover decreased by 18.6%, canopy height by 2.7 m, and NPP by 52.2, while fragmentation increased by 23.0 patches km^{-2}. Crucially, impacts decay to 5 km. The study highlights severe degradation in the Global South, partial recovery in the Global North, and conflicting long-term trends across metrics in 89% of grid cells (Table 2).

Compounding these individual anthropogenic disturbances, wildfire disturbance has emerged as a globally intensifying threat to PA ecological integrity. A 21st-century global assessment reveals that PAs—despite occupying only 19.2% of semi-natural ecosystems—concentrate 28.5% of annual burned area, with internal burned area increasing at +0.46% per year, nearly double the rate of PA area expansion (+0.27% per year) [37]. The disproportional increase is most acute in fire-prone biomes such as Mediterranean and dry tropical forests, tropical grasslands, and xeric shrublands (Table 2).

Table 2 traces the maturation of single-disturbance PA monitoring, from localized inventories to globally consistent, annually resolved evaluations of core pressures (cropland, light pollution, mining, built-up growth, wildfire). A cross-cutting insight is the pervasive buffer zone leakage—pressures in 10-km PA buffers are 2–23 times higher than internal levels across mining, built-up, and light pollution studies—highlighting that management effectiveness must extend beyond PA boundaries. Methodologically, these works demonstrate

that data selection should match disturbance characteristics: harmonized DMSP/VIIRS time series enabled 27-year light pollution trend analysis [28,29], moderate-resolution fire products captured continental burn dynamics, and Landsat/Sentinel-2 data detected subtle land-cover conversions. Optimal choices thus hinge on disturbance signatures rather than uniform pursuit of high resolution.

4.2. RS Monitoring of Integrated Human Disturbance Within PAs

While single-disturbance monitoring offers clarity and precision, the ecological impact of human activities within PAs is inherently cumulative and interactive. Recognizing this, research has progressively shifted toward integrated human disturbance monitoring, which synthesizes multiple disturbance types into composite indices to enable holistic evaluation of management effectiveness.

The theoretical foundation for integrated monitoring rests on constructing comprehensive spatial proxies of human pressure. The Human Footprint (HF) index, which integrates built environments, intensive agriculture, pasturelands, human population density, NTLs, roads, railways, and navigable waterways, has become a widely used framework for global-scale integrated assessment (Table 3). Leveraging this framework, Jones et al. [39] produced the most comprehensive global map of human pressure within PAs to date, demonstrating that 32.8% of global protected land is under intense human pressure. Their analysis further revealed that for PAs designated before the Convention on Biological Diversity was ratified in 1992, 55% have since experienced increases in human pressure, and that these increases were lowest in large, strict PAs—providing rare empirical evidence that management regime itself shapes effectiveness. The study documented emblematic cases of large-scale infrastructure within PA boundaries, including railways through Kenya's Tsavo East and Tsavo West National Parks, oil and gas extraction in Australia's Barrow Island National Park, and illegal settlement with coffee-plantation conversion by over 100,000 people in Sumatra's Bukit Barisan Selatan National Park.

Table 3. Representative studies on RS monitoring of integrated human disturbance within PA.

Index/Framework	Spatial Scale	Data Sources	Methods	Key Findings	Reference
Human Footprint (HF)	Global PAs, 1993–2009	Built environments, cropland, pasture, population density, NTL, roads, railways, waterways	HF map overlay with WDPA; pressure increase attribution	33% of global protected land under intense human pressure; 55% of pre-1992 PAs saw pressure increases	[39]
Temporal Human Pressure Index (THPI)	Global PAs, 1990–2010	Human population density, land transformation, electrical power infrastructure	THPI computation at 10 km^2 resolution; change analysis by IUCN category	Human pressure increased within PAs globally; only categories Ib and III showed declines	[19]
THPI + Counterfactual Matching	12,315 PAs across 152 countries, 1995–2010	THPI components: population density, NTLs, agricultural cover	Pixel-level matching of PA to unprotected area; compound pressure change index	PAs have on average not reduced compound pressure change vs. counterfactuals	[20]
Comprehensive human pressure (HP)/human modification	1687 nature reserves in China, 2000–2020	human settlement, agriculture, transportation, mining, energy production, dams and reservoirs	Overlay HP for China onto NR boundaries; compare HP trends inside NRs vs. nationally	HP inside NRs showed fluctuating downward trends, far below the national average. Stricter management leads to lower HP	[40–42]

Complementary to the HF approach, Geldmann, Joppa and Burgess [19] developed a spatially and temporally explicit map of global change in human pressure between 1990 and

2010, compiling a Temporal Human Pressure Index (THPI) based on human population density, land transformation, and electrical power infrastructure. Their evaluation revealed that human pressure increased within PAs across the globe, with the magnitude of increase varying by location and IUCN management category—only wilderness areas and natural monuments (categories Ib and III) exhibited decreases in pressure.

Building directly upon this THPI foundation, Geldmann, Manica, Burgess, Coad and Balmford [20] advanced the field from mere pressure mapping to rigorous effectiveness evaluation by introducing a counterfactual matching design. They compiled data from 12,315 PAs across 152 countries—covering 81.8% of the global PA estate as of 1995—and tracked a compound index of pressure change over the 15-year period (1995–2010). Crucially, each PA pixel was matched to an unprotected pixel with commensurate soil type, elevation, and initial pressure exposure, enabling the isolation of PA management effect from location bias. Their striking finding was that compared with matched unprotected areas, PAs have on average not reduced the compound index of pressure change over the past 15 years. Extending the counterfactual framework pioneered by Geldmann et al. [20], recent global assessments have begun linking human pressure proxies to ecological outcomes—for instance, Li, Fang, Watson, Sun, Qi, Wang and Liu [24] applied matched counterfactual design to evaluate PA effectiveness in resisting habitat loss, bridging the methodological gap between management and conservation effectiveness dimensions. In tropical regions, pressure change from cropland conversion increased even more inside PAs than in matched unprotected areas—Sub-Saharan grassland cropland increased at nearly double the rate of unprotected land; African mangroves saw 13% more agricultural pressure inside PAs; and remote grassland habitats of Southeast Asia experienced 8% more agricultural increase inside PAs. By contrast, across the Northern Hemisphere and Australia, PAs proved effective at slowing human encroachment relative to counterfactuals. The study further linked PA performance to national-level development scores (HDI) and road density, demonstrating that countries with higher human development indices experienced lower rates of pressure increase within their PAs. This work is particularly significant because, unlike earlier forest-centric RS studies, it explicitly cautioned that relying solely on remotely sensed forest cover metrics can produce a biased picture of PA effectiveness—non-forested biomes such as savannahs and grasslands have been systematically under-assessed.

Table 3 illustrates that integrated disturbance monitoring has evolved along two parallel pathways: (i) globally consistent, remotely sensed proxies (HF, THPI) that enable cross-PA comparability at the expense of fine-grained, PA-specific disturbance typologies; (ii) regionally or nationally customized indices that incorporate local disturbance weights and management thresholds, trading off global comparability for operational relevance. The study by Geldmann et al. [20] represents a methodological leap within pathway (i): by introducing counterfactual matching, it transforms integrated RS from descriptive pressure mapping into causal effectiveness evaluation—isolating the management effect from location bias. Both pathways share a common methodological reliance on multi-source RS data fused on cloud-computing platforms, permitting the operational generation of disturbance maps across thousands of PAs simultaneously.

Nevertheless, integrated remote-sensing assessment of human pressure is not without limitations. A European Union field survey dataset encompassing 8210 PAs has revealed that commonly used remote-sensing-derived indices—such as the HF, Human Modification, and LandScan Global Population Database—do not consistently correlate with threats documented through field surveys. These indices best capture threats associated with urbanization, agriculture, and pollution, but they may miss crucial threats such as hunting and invasive species. This limitation underscores the necessity of complementing RS

assessments with in-situ field surveys whenever possible, particularly for PAs where cryptic or non-land-surface-altering disturbances dominate.

In summary, the progression from monitoring individual disturbances to monitoring integrated human disturbance represents a paradigm shift in the RS evaluation of PA management effectiveness. Individual-disturbance monitoring provides the foundational evidence base and mechanistic understanding of specific threat processes, while integrated monitoring synthesizes these threads into composite indices that align with management and policy needs. Together, they form a multi-scale, multi-temporal, and multi-dimensional technical framework that transcends the spatial and temporal constraints of traditional ground-based surveys, enabling the systematic evaluation of management effectiveness across individual PAs, PA networks, and global PA systems.

5. RS for Conservation Effectiveness of PA

The preceding section established RS as the primary tool for monitoring anthropogenic pressures within PA, quantifying threats ranging from cropland encroachment to light pollution [20,34,39]. However, the mere suppression of detectable disturbance does not automatically guarantee conservation success. A PA may appear structurally intact in a satellite image yet suffer from silent ecological degradation, such as the disappearance of keystone species or the disruption of hydrological cycles. This epistemological gap necessitates a shift from evaluating management effectiveness—the degree to which human pressures are held at bay—to evaluating conservation effectiveness—the degree to which the ecological integrity of the PA is genuinely maintained or restored. The analytical focus thus shifts from anthropogenic pressure proxies to ecological response variables. RS technologies, having evolved from simple land-cover classifiers into sophisticated multi-sensor observatories, now provide the empirical backbone to answer whether ecosystems have actually improved and biodiversity has rebounded. Current research integrates four interlinked dimensions: biodiversity dynamics, ecosystem pattern integrity, ecosystem quality, and ecosystem service provision.

5.1. RS Monitoring of Biodiversity: Proxies, Structural Diversity, and Species Distribution

Biodiversity operates across three hierarchical levels—genes, species, and ecosystems—and RS contributes critical data at each organizational tier [43]. While traditional field campaigns are limited in spatial coverage, particularly in dense tropical forests, marine PAs, and remote alpine regions, satellite and airborne sensors offer the synoptic observation required for large-scale assessments. Current methodological frontiers center on three complementary approaches: species distribution modeling (SDM) as an indirect proxy, spectral diversity as a direct estimator of plant taxonomic richness, and three-dimensional structural complexity as a predictor of habitat suitability (Table 4).

SDM remains the most established avenue for translating RS into biodiversity assessments. By integrating satellite-derived environmental covariates, including vegetation indices, leaf area index, land surface temperature, elevation, and climatic water deficit, with species occurrence records, correlative SDMs generate spatially continuous predictions of habitat suitability. A representative advance comes from the Sanjiangyuan region, where the integration of high-precision habitat factors extracted from Chinese GaoFen satellites significantly refined habitat simulations for the snow leopard (Panthera uncia), reducing the estimated suitable habitat range by approximately 28,000 km^2 compared to coarser global datasets [44]. At the global scale, SDM-driven analyses have consistently revealed significant representation gaps, wherein PAs fail to encompass the full climatic envelopes of threatened species [45].

Alongside SDMs, the Spectral Variation Hypothesis has opened new pathways for direct biodiversity retrieval. This hypothesis posits that the heterogeneity of reflectance spectra within a pixel correlates positively with plant species richness, as different plant species impart distinctive spectral signatures. Schweiger et al. [46] established that plant spectral diversity integrates both functional and phylogenetic components of biodiversity and predicts ecosystem function, providing a theoretical anchor for wall-to-wall biodiversity mapping within PAs. Hyperspectral missions and high-fidelity simulations of broadband sensors have demonstrated robust correlations between spectral diversity and species richness across diverse ecosystems.

The third pillar, structural diversity, has been revolutionized by spaceborne LiDAR. NASA's GEDI mission provides direct measurements of canopy height profiles and vertical foliage distribution [47]. Research demonstrates that GEDI-derived metrics of canopy structural complexity strongly predict biodiversity in tropical forests. The fusion of LiDAR-derived vertical structure with hyperspectral-derived species diversity enables comprehensive inversion of forest species diversity, while the integration of airborne LiDAR, hyperspectral data, and high-resolution imagery offers an efficient solution for monitoring forest composition within PAs [48,49]. Despite these advances, the "wall of complexity" persists: RS excels at detecting plant diversity and vegetation structure but struggles with faunal and microbial diversity (e.g., insects, microbes, many vertebrates), necessitating the integration of acoustic monitoring and environmental DNA sampling [50].

Table 4. Integrated RS dimensions for evaluating conservation effectiveness of PA.

Dimension	Core Indicators	Key RS Data Sources	Representative Applications
Biodiversity	Species richness, habitat suitability, spectral diversity, vertical structure	GaoFen, Sentinel-2, Hyperspectral, GEDI LiDAR	Snow leopard habitat refinement [44]; forest diversity inversion via LiDAR–hyperspectral fusion [48]
Ecosystem Pattern	Landscape fragmentation, connectivity, habitat area ratio	Landsat, Sentinel-2, high-resolution commercial imagery	Effectiveness of global PAs in resisting habitat loss [24]. Redwood NP landscape integrity [51]
Ecosystem Quality	NDVI, EVI, LAI, NPP, VOR metrics, recovery rate	MODIS, Landsat, Sentinel-2, multi-temporal LiDAR	"Greening but weakening" paradox in 431 Chinese reserves [50]
Ecosystem Services	Water yield, carbon storage, soil retention, GEP	MODIS, LiDAR, SAR, InVEST/GWR/RF modeling	Hoh Xil service enhancement [52]; China PA-scale effectiveness [53]; Mediterranean trade-offs [54]

5.2. Monitoring Ecosystem Pattern: Landscape Configuration and Habitat Integrity

Ecosystem pattern refers to the spatial arrangement of land cover and habitats. RS is indispensable for quantifying landscape fragmentation, connectivity, and the spatial integrity of keystone species habitats over decadal timeframes [55,56]. Medium-resolution sensors such as Landsat and Sentinel-2 are extensively deployed to compute landscape metrics, including the Splitting Index, Contagion, and Mean Patch Size, that collectively quantify habitat fragmentation trajectories. Comparative assessments in California's Redwood National Park revealed that while overall forest cover remained stable inside the PA, the connectivity of old-growth patches decreased significantly outside PA boundaries, highlighting the role of PAs in maintaining landscape integrity [51].

At the global scale, Li et al. [24] provided compelling evidence of the 'mixed effectiveness' of PAs in resisting habitat loss, demonstrating that while strict PAs show measurable success in conserving habitat integrity, less-restricted categories exhibit variable performance across biomes. This global assessment echoes the 'greening but weakening' paradox identified in national-scale studies [50], reinforcing that habitat integrity, rather than mere greenness, must serve as the core metric for conservation effectiveness evaluation.

The second major application is keystone species habitat assessment. RS supports habitat suitability evaluation for iconic species such as the giant panda and the Asian elephant. By mapping bamboo distribution dynamics using multi-temporal satellite data, or by monitoring forest–elephant conflict zones via integrated optical and radar data, managers can evaluate whether conservation efforts align with species' ecological requirements [57]. In China, the integration of RS with field data has facilitated the delineation of ecological red lines and the optimization of giant panda conservation corridors, directly informing PA boundary adjustments [58].

5.3. Monitoring Ecosystem Quality: Vegetation Vigor, Structural Complexity, and Restoration Trajectories

Ecosystem quality assesses the physiological status, resilience, and recovery trajectory of vegetation communities. Time-series analysis of MODIS and Landsat archives yields critical indicators such as the Normalized Difference Vegetation Index (NDVI), Enhanced Vegetation Index (EVI), Leaf Area Index (LAI), and Net Primary Productivity (NPP), which serve as proxies for ecosystem vigor.

A national-scale assessment of 431 national nature reserves in China from 1990 to 2020 applied a Vitality–Organization–Resilience framework, revealing a paradoxical "greening but weakening" trajectory [50]. While 60.3% of PAs maintained healthy ecosystems and vegetation vitality increased by 29.4%, ecosystem organization declined by 6.1% and resilience plummeted by 26.8%. Forest ecosystems exhibited a 9.9% decrease in organization, whereas grasslands showed a 7.4% increase—demonstrating that different biomes respond to protection management in fundamentally divergent ways. This finding delivers a cautionary message: single greenness-based metrics can mask substantive functional degradation, necessitating multi-dimensional assessment frameworks.

Beyond two-dimensional greenness, LiDAR and radar (SAR) sensors quantify structural attributes invisible to passive optical sensors. In mine rehabilitation sites within PAs, multi-temporal LiDAR surveys track the recovery of canopy height and ground surface roughness [59]. Similarly, high-resolution imagery aids in monitoring the success of ecological engineering projects, such as the "Grain for Green" program, by verifying the return of native vegetation structure.

5.4. RS Monitoring of Ecosystem Services: Spatially Explicit Valuation and Effectiveness Verification

The evaluation of conservation effectiveness attains its most policy-relevant expression in the assessment of ecosystem services. Recent systematic reviews underscore that while the field of ecosystem service mapping in PAs has expanded, significant heterogeneity remains in methodologies and indicator selection [60,61]. RS enables the spatially explicit quantification of multiple service categories: water conservation, carbon sequestration, soil retention, and sandstorm prevention.

At the individual PA scale, empirical evidence is accumulating. Zeng et al. [52] evaluated whether PA improves ecosystem services through a case study of the Hoh Xil Nature Reserve, providing direct evidence that protection translates into measurable service enhancement. In the Xilingol Grassland National Nature Reserve, RS assessments demon-

strated that conservation efforts partially mitigated climate-induced declines in service value, although a general downward trend persisted [62]. Conversely, in the Tomur Peak National Nature Reserve, multi-temporal Landsat imagery revealed that reductions in water bodies and forests led to an overall decrease in total ecosystem service value, highlighting the urgency of strengthened protection [63].

Moving beyond individual case studies, Yu et al. [53] provided a macro-scale assessment of the effectiveness of China's PAs in enhancing ecosystem services, offering a rare national-level quantification. Critically, the relationship between protection, services, and biodiversity is not automatically synergistic. Lecina-Diaz et al. [54] examined Mediterranean forests and shrublands, concluding that protection alone does not guarantee concurrent gains in both ecosystem services and biodiversity, as management regimes may favor certain services at the expense of others. This finding underscores that RS evaluations must adopt multi-indicator frameworks to capture potential trade-offs between ecological functions. The integration of RS products with advanced analytical models and algorithms—such as the InVEST model, geographically weighted regression, and random forest—represents a frontier in calibrating Gross Ecosystem Product (GEP) calculations against satellite-derived indices.

5.5. Synthesis: Toward an Integrated RS Framework for Conservation Effectiveness

The evolution of RS in PA evaluation reflects a maturation from single-metric assessments to integrated frameworks. Early studies focused on static land cover (Pattern), progressing to vegetation greenness (Quality), then to carbon and water fluxes (Function), and ultimately to integrating these with biodiversity proxies (Conservation Effectiveness). Table 4 summarizes these integrated dimensions.

6. Challenges and Prospects

The preceding sections have demonstrated the transformative potential of RS in evaluating PA effectiveness, yet persistent gaps remain between technological capability and operational conservation needs. This section builds on the core limitations identified across the literature and outlines forward-looking directions aligned with the Post-2020 GBF and the "30 × 30" target (Figure 4).

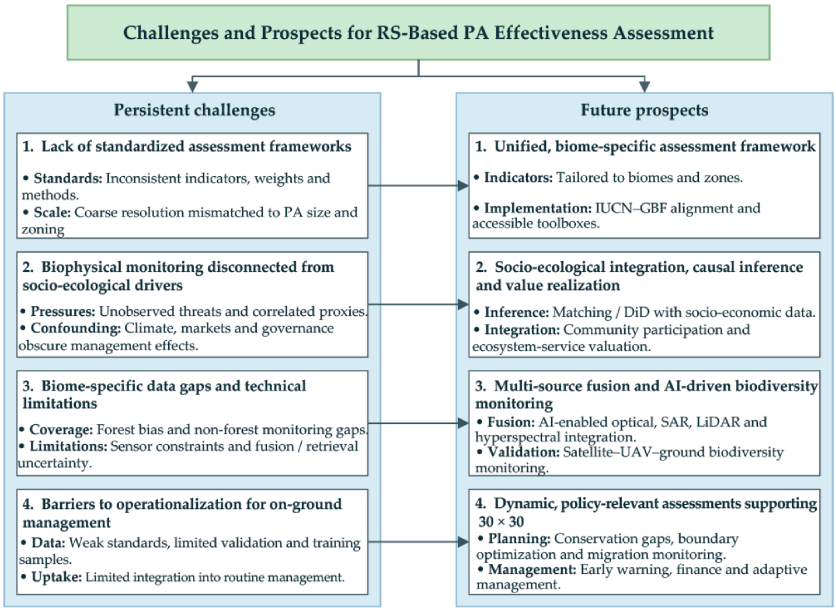


Figure 4. Persistent challenges and future directions in RS-based assessment of PA effectiveness.

6.1. Persistent Challenges

6.1.1. Lack of Standardized, Globally Applicable Assessment Frameworks

A critical barrier highlighted by multiple reviews is the absence of a unified, cross-context assessment framework for RS-based PA evaluation. Gohr et al. [14] explicitly note that existing remotely sensed effectiveness assessments lack common methodological standards, leading to high heterogeneity in indicator selection, spatial resolution, and analytical approaches across studies [60,61]. For instance, composite pressure indices such as the HF [64] and the Human Modification Index [41] assign varying weights to disturbance components, making cross-PA and cross-national comparisons unreliable.

A further critical limitation lies in the frequent mismatch between RS-derived pressure indices and ground-validated threats. While RS excels at detecting biophysical changes—such as vegetation loss, encroachment, or infrastructure expansion—many threats to PAs are either invisible to optical or radar sensors or manifest at spatial and temporal scales that RS cannot resolve. For example, poaching leaves no consistent spectral signature; invasive species may alter ecosystem function without immediate canopy-level changes detectable by satellite [65]; noise pollution and extensive grazing often operate below the detection threshold of coarse-resolution sensors or mimic natural disturbance regimes [66]. Consequently, RS-based assessments may systematically underestimate or mischaracterize actual threat levels, creating a false sense of conservation security when pressure indices appear favorable [67]. In addition, most global human pressure datasets treat extensive livestock grazing (pasture) as a static land use class, despite its dynamic spatial extent and significant ecological impact. The coarse spatial resolution of these datasets (typically 1 km) also renders them ineffective for the majority of small-sized PAs worldwide, and unable to account for the differentiated management requirements of internal PA zoning (e.g., core zones vs. buffer zones). This scale mismatch undermines the alignment of technical assessments with IUCN PA classification objectives and practical governance needs.

Compounding the absence of unified evaluation standards, published assessments of PA effectiveness often reach conflicting conclusions. These inconsistencies arise from both genuine heterogeneity in real PA performance and study-specific analytical decisions, and can be attributed to seven interrelated factors (Figure 5). Biome type influences detectability. Remote-sensing methods work well for forest deforestation but may underestimate subtle degradation in grasslands, savannas and other open ecosystems. IUCN management categories and zoning further shape outcomes. Strict PAs (IUCN Ia–Ib) typically outperform multiple-use PAs (V–VI), though many global analyses combine all designations and obscure this difference. Counterfactual study design is a major methodological driver. Simple before–after comparisons tend to overestimate effectiveness owing to non-random PA placement, whereas matched controls yield different results conditioned on the chosen covariates. Indicator selection is another key source of disagreement. Conflating metrics of management effectiveness for human pressure reduction and conservation effectiveness for ecosystem resilience and structural integrity, or overreliance on greenness proxies such as NDVI, may hide the "greening but weakening" paradox. Spatial resolution introduces scale-dependent bias. Coarse datasets fail to resolve fine disturbances within smaller PAs and distort effectiveness estimates. The duration of the time series also matters. Short records capture episodic land-use shocks, while longer time series reveal gradual cumulative degradation and may reverse inferred effectiveness. Finally, socio-economic and institutional context creates real performance variation. Stronger outcomes are generally observed where enforcement and governance capacity are high. Together, these seven dimensions explain much of the inter-study inconsistency.

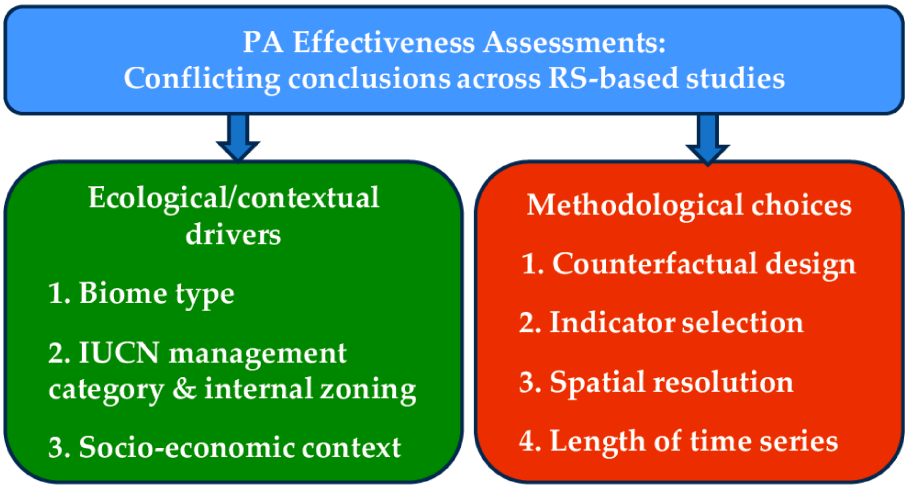


Figure 5. Categorization of seven key drivers contributing to divergent empirical outcomes in PA effectiveness assessments.

6.1.2. Disconnect Between Biophysical Monitoring and Socio-Ecological Drivers

Most RS-based evaluations focus exclusively on biophysical indicators (e.g., vegetation greenness, land cover change) while neglecting the socio-economic drivers that ultimately determine conservation outcomes. Geldmann et al. [20] demonstrate that RS-derived pressure indices often fail to correlate with ground-validated threats such as poaching, invasive species, and unsustainable resource extraction. Methodological challenges further complicate composite pressure mapping: collinearity among input variables (e.g., population density, NTLs, and road infrastructure) can lead to overestimation of human pressure in areas where multiple correlated stressors co-occur [9,68], skewing effectiveness evaluations. Additionally, the net effect of PA management is rarely isolated from confounding drivers such as climate variability, market-driven land use changes, or exogenous policy shifts, limiting the credibility of causal claims about conservation success [8,17,69]. The social dimension of conservation—including community livelihoods, governance quality, and management investment—also remains largely unintegrated into RS assessment systems, despite its well-documented influence on PA performance.

6.1.3. Biome-Specific Data Gaps and Technical Limitations

Current RS methodologies are heavily biased toward forest ecosystems, leaving non-forest biomes chronically under-assessed [70]. Geldmann et al. [20] caution that savanna, grassland, wetland, and desert ecosystems are systematically overlooked in global RS evaluations, partly because most disturbance detection algorithms are optimized for forest structural changes and perform poorly in open-canopy systems. Technical constraints further exacerbate these gaps: optical sensors are hindered by persistent cloud cover in tropical and monsoon regions, while high-resolution, hyperspectral, and spaceborne LiDAR data remain cost-prohibitive for most PA authorities. Multi-source data spatiotemporal matching also introduces significant uncertainty, particularly in complex terrain. Even advanced sensors have inherent limitations: single-band LiDAR scanning achieves high classification accuracy in structurally distinct forest types (e.g., coniferous vs. broadleaf mixes) but performs poorly in species-rich mixed forests where structural differences between taxa are minimal [71]. Inversion of key ecological parameters such as NPP, soil moisture, and above-ground biomass also suffers from high error rates in mountainous and wetland ecosystems, where topographic effects and signal saturation interfere with retrieval accuracy. Non-structural disturbances such as noise pollution—known to disrupt

wildlife migration and breeding—remain entirely unmonitored by current RS platforms [72], representing a critical blind spot in disturbance assessments.

6.1.4. Barriers to Operationalization for On-Ground Management

While cloud-computing platforms such as GEE have lowered technical barriers to RS data processing, significant implementation gaps persist for on-ground PA managers, particularly in developing countries [73]. First, tool accessibility remains a challenge: many advanced RS models and cloud-computing platforms require specialized software or high-performance hardware that is often unavailable in resource-limited PA management agencies. Second, training requirements are substantial; interpreting RS outputs and integrating them into management decisions demands technical expertise that local rangers and managers frequently lack. Third, data-access costs can be prohibitive: while coarse-resolution satellite data are increasingly open, high-resolution imagery, commercial datasets, and cloud-processing credits often entail fees that strain already limited PA budgets. Fourth, ground-validation constraints persist—systematic field data are essential for calibrating RS-derived pressure indices, yet field campaigns in remote or insecure PAs are logistically difficult and personnel-intensive. Addressing these barriers will require targeted capacity-building, development of lightweight open-access tools, and sustained funding mechanisms to bridge the research–management gap in low- and middle-income countries. As a result, cutting-edge RS technologies often remain confined to academic studies rather than being integrated into routine PA management workflows, failing to address the 18.29% global PA management effectiveness assessment gap identified in the Protected Planet Report 2020 [74].

6.2. Future Prospects

6.2.1. Developing a Unified, Biome-Specific Global Assessment Framework

The path forward requires a tiered, biome-specific assessment framework aligned with both scientific rigor and management needs. Building on the dual-dimensional logic (management effectiveness + conservation effectiveness) established in this review, standardized indicator sets should be tailored to major biomes: forest PAs could prioritize canopy structural complexity, spectral diversity, and carbon stock; grassland and savanna PAs could emphasize vegetation cover stability, productivity resilience, and habitat connectivity; wetland PAs could focus on hydrological regime dynamics and inundation extent; and marine PAs could center on benthic habitat health and anthropogenic pressure monitoring. Critically, this framework must accommodate the differentiated management requirements of PA internal zoning, with adjustable indicator weights for core, buffer, and experimental zones to reflect varying levels of permitted human activity. The framework should be formally integrated with IUCN PA management effectiveness tools [13] and the GBF monitoring system [4], supported by open-access GEE plugins and low-code toolboxes to reduce technical barriers. Such standardization would enable globally comparable assessments, filling the critical data gap in the Protected Planet series and supporting evidence-based policy decisions.

6.2.2. Advancing Multi-Source Fusion and AI-Driven Holistic Biodiversity Monitoring

Overcoming current technical limitations demands tighter integration of multi-source RS data and AI. Fusing optical, SAR, LiDAR, and hyperspectral data can compensate for individual sensor shortcomings—for example, combining SAR's all-weather capability with LiDAR's 3D structural information to monitor cloud-prone tropical ecosystems and open-canopy biomes. Deep learning architectures such as vision transformers and graph neural networks can improve detection of small-scale disturbances, e.g., illegal mining,

unregulated trails, and subtle biodiversity signals. Transfer learning and foundation models will be critical for addressing the "small sample problem" in data-scarce PAs, enabling cost-effective model transfer from well-monitored regions to understudied areas. Exploration of emerging technologies such as quantum RS may further expand observational capabilities for previously unmonitored stressors like noise pollution. Critically, RS must be embedded in integrated monitoring networks: satellite sensors provide landscape-scale screening, drones enable high-resolution hotspot verification, and ground-based sensor networks (camera traps, acoustic monitors, eDNA samplers) deliver direct biodiversity validation, closing the loop between remote proxies and on-ground ecological reality.

6.2.3. Supporting the "30 × 30" Target with Dynamic, Policy-Relevant Assessments

RS will play an indispensable role in implementing the GBF's "30 × 30" target. At the strategic level, RS can identify terrestrial and marine conservation gaps, evaluate the effectiveness of existing PAs, and inform boundary adjustments or new PA designations to maximize biodiversity representation. Transboundary migratory species monitoring offers a particularly compelling use case: RS-derived telemetry data can map full-lifecycle migration corridors—for example, tracing a shorebird's route from Arctic breeding grounds through East Asian tidal flats to Australasian wintering sites—making conservation responsibilities visible to all range countries and driving implementation of multilateral agreements such as the Convention on Migratory Species [75]. At the operational level, near-real-time RS products (e.g., weekly disturbance alerts, monthly ecosystem health indices) can power early warning systems for threats such as wildfires, deforestation, and invasive species outbreaks, enabling adaptive management responses. Linking RS-derived effectiveness metrics to policy instruments—such as performance-based conservation finance, ecological compensation, and PA funding allocation—will ensure that technical assessments translate into tangible conservation incentives, as demonstrated by recent national-scale pressure trend analyses in China [18].

6.2.4. Integrating Socio-Ecological Dimensions for Causal Inference and Value Realization

Future research must move beyond correlative assessments to causal inference, adopting methods such as counterfactual matching [20] and difference-in-differences [9,76] to isolate the net impact of PA management from confounding drivers. Integrating RS data with socio-economic datasets, e.g., points of interest, population mobility, policy texts, and household livelihood surveys, will enable holistic analyses of how governance, community engagement, and external pressures interact to shape conservation outcomes. Community participation should be prioritized: training local rangers and residents to use portable RS tools such as lightweight drones and smartphone-based monitoring apps can reduce data collection costs, improve ground validation sample representativeness, and strengthen community co-management capacity. Furthermore, RS can underpin the valuation of ecosystem services to support ecological product value realization—for instance, coupling RS-derived biomass estimates with carbon market mechanisms, or linking habitat quality metrics to ecotourism revenue models [77]. This integration will make the benefits of PA protection economically tangible, strengthening the business case for long-term conservation investment.

Addressing these challenges and realizing these prospects will require sustained collaboration between RS scientists, conservation practitioners, and policymakers. By bridging technical innovation and governance needs, RS can fulfill its potential as a cornerstone of global conservation effectiveness evaluation, directly contributing to the success of the Post-2020 GBF and the long-term sustainability of PA networks worldwide.

7. Advantages and Limitations

7.1. Comparative Advantages

To explicitly address how the proposed dual-dimensional analytical framework differs from existing analytical frameworks in the field of RS applications in PAs, we provide a comparative positioning of this review against selected existing syntheses (Table 5).

Table 5. Comparative positioning of this review against selected existing reviews on RS applications in PAs.

Review	Primary Focus	Management vs. Conservation Effectiveness Separated?	RS Technology Stack Synthesized?	Linked to PA Governance
Luo et al. [18]; Morfopoulou et al. [78]	Human pressure mapping	Pressure only	Partial (mostly pressure proxies)	Partially (SDG 15)
Santos Silva et al. [31]	PA effectiveness, RS methods	Ecosystem processes only	Yes	Weak
Kalinauskas et al. [60]	ES mapping in PAs	Ecosystem services only	No	Weak
Pu et al. [61]	ES research in PAs	Ecosystem services only	Partial	Decision-making mention
Reddy [21]	Biodiversity RS	Biodiversity only	Method-level	No PA governance link
Wang & Gamon [22]	Plant biodiversity RS	Biodiversity only	Spectral/LiDAR methods	No
McCarthy et al. [2]	SDG 13/14/15 in PAs	Implicit	Yes	Strong (SDG framing)
This review	Dual-dimensional: management + conservation effectiveness	Explicit two-axis framework	Yes	Strong (IUCN PAME + GBF "30 × 30")

As shown in Table 5, existing reviews exhibit notable limitations in scope and framework structure. For instance, Luo et al. [18] and Morfopoulou et al. [78] primarily focus on human pressure mapping without separating conservation outcomes. Santos Silva et al. [31] and McCarthy et al. [2] address PA effectiveness but limit their scope to ecosystem processes or implicit SDG framings, respectively. Similarly, Kalinauskas et al. [60] and Pu et al. [61] concentrate solely on ecosystem services, while Reddy [21] and Wang & Gamon [22] focus exclusively on biodiversity RS. Most of these works lack an explicit separation of management and conservation effectiveness, and their links to PA governance remain weak or disconnected.

In contrast, this review introduces an explicit two-axis framework that simultaneously integrates management effectiveness and conservation effectiveness. Furthermore, this review synthesizes a comprehensive RS technology stack and strongly aligns with PA governance frameworks, specifically linking to IUCN PAME and the Kunming-Montreal GBF "30 × 30" targets. This dual-dimensional structure and strong governance connection highlight the unique contribution and added value of our analytical framework.

7.2. Limitations

Three limitations of this review should be acknowledged when interpreting its findings. First, the literature search employed a focused Boolean strategy built around four core dimensions—RS technology, PAs, anthropogenic pressure/ management, and ecological outcomes. While this captured the most representative publications, it did not exhaustively enumerate all possible synonyms or subcategory terms. For instance, specific anthropogenic disturbance types (e.g., selective logging [79], artisanal mining [80], thermal pressure from urbanization [81], or recreational trampling [82]) are represented through their broader parent terms rather than through dedicated sub-keywords. Consequently, niche studies employing unconventional terminology may have been missed. Second, the search was

conducted exclusively in the Web of Science Core Collection, which is predominantly indexed in English. Publications in other languages—including Chinese, Spanish, Portuguese, and French, which collectively represent substantial PA research output in biodiversity-rich regions—were not retrieved. This may partially explain the geographic concentration observed in Section 2.3, where the top five countries account for 47.3% of the corpus. Third, the dimensional publication counts reported in Section 2.3 should be interpreted as relative indicators of research attention rather than absolute tallies of all eligible studies. The counts serve to illustrate the broad distribution of topical focus within the retrieved sample and to contextualize the evidence base, but they do not claim exhaustive coverage of the global literature. Future systematic reviews with expanded keyword sets and multilingual databases would be valuable to refine these estimates.

8. Conclusions

This review addresses the long-standing disconnect between RS advances and practical PA governance by proposing a dual-dimensional framework integrating management effectiveness and conservation effectiveness. This structure addresses the fragmentation of prior syntheses—which either prioritized ecological monitoring decoupled from management contexts or focused on threat mapping without linking to holistic performance evaluation.

We demonstrate that RS has evolved from a supplemental mapping tool to a major component of large-scale PA evaluation. For management effectiveness, monitoring has progressed from single-disturbance tracking to integrated pressure assessments, with counterfactual approaches now capable of isolating the net conservation effect of PA designation from confounding drivers. For conservation effectiveness, assessments have moved beyond single greenness metrics to multi-dimensional frameworks covering biodiversity dynamics, ecosystem quality, and service provision, supported by breakthroughs in spaceborne LiDAR and hyperspectral sensing.

Persistent challenges nonetheless constrain operational application: standardized, biome-specific assessment frameworks remain lacking, leaving small PAs and non-forest ecosystems under-evaluated; cryptic disturbances such as extensive grazing and noise pollution are still unmonitored by current sensors; and gaps between academic RS tools and on-ground management needs limit technology uptake in data-scarce regions. Moving forward, the field must prioritize developing tiered, context-adaptive indicator systems, advancing AI-driven multi-source data fusion to address technical bottlenecks, and streamlining technology transfer to frontline managers. As countries implement the post-2020 GBF's "30 × 30" target, RS will remain a key tool for transparent, scalable PA performance monitoring. Closing the loop between technological innovation and governance needs is essential to ensure that global conservation investments yield tangible, lasting benefits for biodiversity and people.

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Abbreviations

The following abbreviations are used in this manuscript:

PA/PAs	Protected Area(s)
RS	Remote Sensing
GBF	Kunming-Montreal Global Biodiversity Framework
LiDAR	Light Detection and Ranging
MODIS	Moderate-resolution Imaging Spectroradiometer
NDVI	Normalized Difference Vegetation Index
LAI	Leaf Area Index
NPP	Net Primary Productivity
EVI	Enhanced Vegetation Index
NTL	Nighttime Light
VOR	Vigor–Organization–Resilience
SDM	Species Distribution Modeling
GEDI	Global Ecosystem Dynamics Investigation
GWR	Geographically Weighted Regression
RF	Random Forest
AI	Artificial Intelligence
GEE	Google Earth Engine
GEP	Gross Ecosystem Product
SAR	Synthetic Aperture Radar
THPI	Temporal Human Pressure Index
HF	Human Footprint
IUCN	International Union for Conservation of Nature

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