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TOPICAL REVIEW

The role of GEDI spaceborne lidar in biodiversity analyses: a topical review

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Abstract

Biodiversity underpins ecosystem resilience and human well being, yet conventional field inventories alone cannot monitor its rapid change across large areas. Earth observation fills this gap by providing consistent, repeatable measurements for assessing biodiversity change. Lidar is particularly well suited to biodiversity assessment because it captures three dimensional (3D) vegetation structure, which is linked to habitat complexity. The Global Ecosystem Dynamics Investigation (GEDI) spaceborne lidar mission delivers consistent, globally distributed 3D structure measurements, enabling explicit inference at extents unattainable from aircraft. Here we review 29 studies that use GEDI for biodiversity assessment across ecosystems and taxa. We first map geographic and ecosystem coverage, then synthesize how GEDI data have been used for evaluating aspects of biodiversity. We next assess approaches to link GEDI information and biodiversity variables, and evaluate which aspects of biodiversity have been targeted and their effectiveness. We discuss key limitations and chart future directions, including hypothesis driven data fusion, uncertainty propagation, and cross mission synergies. We find that the use of GEDI for biodiversity applications has increased steadily since 2019, where most work has focused on alpha diversity and species–habitat relationships in forest ecosystems, with a strong emphasis on birds and trees. GEDI structural metrics are commonly fused with complementary predictors from optical, radar, topography, and climate datasets for continuously mapped structure measures, which generally improves model performance relative to GEDI only inputs. By contrast, applications of beta/gamma taxonomic patterns, functional or phylogenetic diversity, non forest systems, and other taxa (e.g. bats, insects, small mammals) remain rare and are represented mainly by isolated case studies. Most analyses are conducted at local to regional scales thus global assessments are still limited. Key methodological gaps include standardized *in-situ* validation, explicit uncertainty treatment, and temporal analyses beyond single snapshots. Overall, GEDI has become a valuable baseline for biodiversity assessment, yet broader uptake—particularly across ecosystems, taxa, and scales—will benefit from continued multi sensor fusion, improved validation frameworks, and follow on spaceborne lidar missions with greater spatial continuity and accuracy.

1. Introduction

With human activities reshaping global ecosystems and governments striving to confront the escalating biodiversity crisis, the establishment of effective systems for monitoring biodiversity has become increasingly essential (Reddy 2021). Following the adoption of the Convention on Biological Diversity (CBD) in 1992, a series of international agreements have endeavored to tackle biodiversity loss and establish a framework for global governance (Fajardo del Castillo 2021). The Aichi Biodiversity Targets (2011–2020), developed under the CBD, aimed to significantly reduce biodiversity loss by 2020 (Nguyen and Vuong 2021), yet were mostly not achieved, highlighting the persistent gap between global commitments and implementation (Convention on Biological Diversity 2020). The Kunming–Montreal Global Biodiversity Framework (2022) outlined a new set of global targets to restore nature and halt biodiversity decline by 2030 (Hughes and Grumbine 2023). Additionally, Sustainable Development Goal 15 under the UN 2030 Agenda calls for the protection, restoration, and sustainable use of terrestrial ecosystems and forests, and the urgent need to halt biodiversity loss (Halkos and Gkampoura 2021). These international efforts recognize that biodiversity is a cornerstone of ecosystem resilience and human well being, and emphasize the need for innovative monitoring systems to track ecological change and guide conservation strategies (Reddy 2021). Earth observation (EO) provides consistent, scalable measurements of environmental characteristics that reflect biodiversity, enabling indirect modeling and monitoring of biodiversity patterns (and changes). Field surveys provide highly accurate and detailed observations, including of organisms that cannot be detected remotely, but they are inherently labor intensive and necessarily limited in spatial extent (Rocchini *et al* 2019). In addition, field based monitoring strategies vary substantially within and among countries, often resulting in fragmented and non standardized datasets, further hindered by the absence of coherent data sharing policies (Rocchini *et al* 2019). In recent decades, EO technologies have offered the ability to collect consistent, repeatable, and cost effective data across large areas and at regular intervals. Technological advancements in sensor resolution and sensitivity, coupled with increasing computational capacity, have greatly expanded the potential of EO for ecological applications. Furthermore, changes in data access policies—particularly the increasingly widespread availability of free and open access satellite data—have democratized the use of EO, making it more economically viable and globally accessible (Nagendra 2001, Radeloff *et al* 2024, Chen *et al* 2025). Notably, this has been underpinned by the availability of systematically generated science products and analysis ready datasets. EO systems are playing an increasingly important role in global biodiversity monitoring initiatives through, for example, the collaboration between the Group on EOs Biodiversity Observation Network (GEO BON) and the Intergovernmental Science Policy Platform on Biodiversity and Ecosystem Services (IPBES). Many GEO BON scientists actively contribute to IPBES processes and act as observers in IPBES plenary sessions, ensuring that EO based knowledge directly supports international biodiversity science and policy (Pörtner *et al* 2021). A wide range of remote sensing platforms have been used to estimate various biodiversity components in different ecosystems, using diverse approaches tailored to the ecological questions and spatial scales involved (Cavender-Bares *et al* 2022). Passive sensors, including digital aerial photography, multispectral imagery from uncrewed aerial vehicles (UAVs) and satellites, and airborne imaging spectroscopy have been extensively applied to assess some aspects of alpha (or 'local scale') biodiversity across forest, grassland, and agricultural landscapes (Yin *et al* 2018, Cavender-Bares *et al* 2022, Torresani *et al* 2024b). However, passive sensors are constrained by cloud cover, daylight availability, sensor saturation in dense vegetation, and the timing of image acquisition. Seasonal phenology, soil background reflectance, and atmospheric conditions can further complicate the relationship between spectral signals and field biodiversity data (Gholizadeh *et al* 2018, Gamon *et al* 2020). Although some of these factors can also affect active sensors, their influence is generally weaker or operates through different mechanisms. Active remote sensing technologies, such as lidar (LIght detection and ranging) and radar (RAdio detection and ranging), have therefore gained traction and demonstrated strong potential in quantifying vegetation structural attributes that are closely linked to key aspects of biodiversity (de Conto *et al* 2024), including species composition, habitat complexity, and ecosystem functioning (Vierling *et al* 2008, Vogeler and Cohen 2016, Pillay *et al* 2022). Among these, lidar stands out for its ability to capture the three dimensional (3D) structure of ecosystems—such as canopy height heterogeneity, structural diversity and understory complexity—which are important variables for assessing species richness and other biodiversity indicators (Hakkenberg and Goetz 2021, Moudrý *et al* 2021, Torresani *et al* 2024a, Kacic *et al* 2025). Most studies that have assessed biodiversity using lidar technology have traditionally relied on airborne laser scanning (ALS), which offers relatively high resolution structural information at local to regional scales (Goetz *et al* 2010, Vogeler *et al* 2014, Guo *et al* 2017). More recently, the growing availability and affordability of UAVs equipped with lidar sensors has led to an increase in studies using ultra high resolution 3D data, while terrestrial laser scanning captures extremely detailed and accurate maps of subcanopy vegetation structure (Palace *et al* 2016, Peng *et al* 2021, Tian *et al* 2023). However, expanding these approaches to larger scale biodiversity studies remains challenging due to variability in sensor types, and survey designs, and logistical and cost constraints (Kissling *et al* 2024).

A major advancement in monitoring vegetation structure at near global extent came with the launch of NASA's Global Ecosystem Dynamics Investigation (GEDI), a dedicated spaceborne lidar mission designed to collect detailed 3D structural information on terrestrial vegetation (Dubayah *et al* 2020). The instrument was installed on the International Space Station (ISS) in December 2018 and began acquiring data in March 2019. GEDI remained operational for nearly four years, until March 2023, when it was removed from the ISS and placed into storage. After a year long hibernation, the instrument was reinstalled, resumed data collection in April 2024, and is expected to operate for the duration of the ISS lifespan. GEDI acquires terrestrial observations between 51.6° N and 51.6° S, and provides unprecedented insights into vegetation structure. The instrument emits 1064 nm laser pulses and acquires full waveform returns over discrete footprints approximately 25 m in diameter, spaced roughly 60 m along track and 600 m across track. While other NASA laser altimetry missions like Ice, Cloud, and Land Elevation Satellite-2 (ICESat 2) have notable potential for biodiversity monitoring (Schutz *et al* 2005), only GEDI was designed specifically to measure canopy structure for terrestrial carbon cycle and biodiversity applications. GEDI provides detailed structural metrics—such as canopy height, vertical foliage density profiles—derived from full waveform lidar returns (Dubayah *et al* 2021). These products have supported canopy structure mapping at multiple scales, enabling the creation of regional and global canopy height models (CHMs) through gridded footprint aggregation (Burns *et al* 2024) and the creation of continuous fine resolution maps via fusion with other remote sensing sources, including airborne lidar, radar, and optical imagery (e.g. Landsat (Potapov *et al* 2021), Sentinel-2 (Lang *et al* 2023), Maxar/Vivid2 mosaics (Tolan *et al* 2024)) or by combining multiple sensor types—such as both optical and SAR data (Vogeler *et al* 2023, Filippelli *et al* 2025, de Conto *et al* 2026). These products have been used to meet GEDI's core science requirement, to generate global aboveground biomass estimates at a 1 km resolution with a precision less than 20% of the mean (Dubayah *et al* 2022, Bruening *et al* 2023) but also to support a range of related ecological analyses. These include ecosystem extent mapping (Geremew *et al* 2023), modeling of future forest composition and structure (Chang *et al* 2025), forest structure monitoring (Rishmawi *et al* 2021, Mandl *et al* 2023, Doyle *et al* 2025), forest growth assessment (Liu *et al* 2022, 2025), forest fuels classification (Hoffrén *et al* 2023) and evaluation of fire severity impacts on forest structure and biomass (Guerra-Hernández *et al* 2024). Additionally, GEDI has been used to estimate forest canopy cover (Liu *et al* 2025, Seyrek *et al* 2025), vegetation density (Xi *et al* 2022), foliage height diversity (FHD) (Diaz-Kloch and Murray 2024), and forest disturbances (Holcomb *et al* 2024, Percival *et al* 2024, Clark *et al* 2025). Early investigations had already simulated GEDI like data to test structural proxies for biodiversity (Quinn *et al* 2024). Following GEDI's operational phase, these efforts evolved into applied studies using actual mission data across multiple ecological contexts.

In this review, we adopt a broad and integrative definition of biodiversity, encompassing taxonomic, functional, and phylogenetic dimensions. Because the GEDI literature includes both species specific habitat or occurrence models and studies quantifying community level diversity, we explicitly consider species specific analyses as part of the biodiversity domain. These models do not represent alpha diversity in a narrow sense, but they operate at the same site level spatial scale and are therefore grouped with alpha level information for the purpose of synthesis (table 1).

No comprehensive synthesis has yet been conducted on the use of GEDI for biodiversity assessment. With GEDI now providing several years of global lidar observations and an increasing number of studies evaluating habitat—and biodiversity–structure relationships, this is an opportune moment to synthesize emerging evidence. This review aims to fill that gap by providing an in depth evaluation of the advances, challenges, and knowledge gaps associated with using GEDI data to map and monitor biodiversity. The paper is structured as follows: (i) an introduction contextualizing the relevance of biodiversity monitoring and remote sensing; (ii) a literature search and overview section outlining the search

Table 1. Definitions of alpha, beta, and gamma diversity as applied in this review.

Diversity type	Definition
Alpha diversity	Refers to the diversity of species found within a single, localized site or ecosystem. It captures richness and evenness and is commonly measured using indices such as species richness, Shannon's H, Simpson's D, or Pielou's J. In this review, we also include species specific habitat or occurrence models as 'alpha level information', because they operate at the same site level spatial scale even though they are not diversity metrics in the strict sense.
Beta diversity	Describes the variation in species composition between different habitats or sites within a region. It reflects compositional turnover or dissimilarity across space.
Gamma diversity	Represents the overall species diversity across a broad geographical area or landscape, integrating multiple communities or habitat types.

strategy, selection criteria, and initial findings; (iii) an overview of the ecosystems and geographic contexts in which GEDI has been applied to assess different aspects of biodiversity; (iv) an analysis of how GEDI data have been used in biodiversity studies, distinguishing between early simulated applications and later analyses based on real GEDI observations, including the frequent integration of complementary remote sensing and environmental datasets; (v) a synthesis of the biodiversity dimensions (alpha, beta, gamma, functional, phylogenetic) and the diversity metrics most commonly investigated with GEDI; (vi) a discussion of current limitations and uncertainties, followed by future perspectives; and (vii) concluding remarks.

2. Systematic literature review and overview

2.1. Literature review methodology

A systematic literature review following the PRISMA protocol (Takkouche and Norman 2011) was conducted to identify studies using GEDI data for biodiversity applications (figure 1). The search was performed on the Web of Science platform using the following query (covering publications up to 21 October 2025): TS = (GEDI AND (biodiversity OR 'species distribution' OR 'species richness' OR 'species diversity' OR 'species composition')). The same search logic was applied to Scopus (TITLE-ABS-KEY (GEDI AND (biodiversity OR 'species distribution' OR 'species richness' OR 'species diversity' OR 'species composition'))) and complemented by a targeted Zotero database search. By including a combination of general biodiversity terms (e.g. 'biodiversity', 'species diversity') and more specific ecological indicators (e.g. 'species richness', 'species distribution', 'species composition'), the query maximized sensitivity while maintaining relevance to the scope of this review. We then complemented our search with a targeted exploration of the Zotero GEDI Peer Reviewed Publications group database. After a thorough screening process, we selected a first core set of relevant articles. Studies were included if they explicitly used GEDI data (or GEDI simulated waveforms) to assess biodiversity or related ecological attributes (e.g. species diversity or community structure). Publications that only used GEDI for biomass estimation or general forest structure analysis without a biodiversity component were excluded.

For each paper, we extracted key information including: (i) ecosystem studied (natural and semi natural forests, urban forests, urban areas more broadly, and mixed ecosystems—the latter referring to landscapes where different land covers co occur, such as forest, shrublands, grasslands, or agricultural mosaics); (ii) the extent of analysis (defined as the scale of analysis: local—plot level or site specific studies, typically tens to hundreds of meters; regional—subnational to national analyses, spanning thousands of hectares to several hundred thousand square kilometers; continental and global—cross country or worldwide assessments); (iii) remote sensing data used (GEDI only or GEDI combined with other data sources); (iv) type of *in situ* biodiversity data (if any) and *in-situ* diversity indices (if any); (v) study goal, main findings and analytical approach used. A final summary table compiling all extracted information, including study location, ecosystem type, GEDI data characteristics (e.g. data level, metrics, and integration with ancillary datasets), study objectives, analytical approaches, biodiversity data and indices, and spatial scale—together with effectiveness classifications, is provided in the appendix.

2.2. Summary of findings

A total of 125 unique records were retrieved across databases from 101 Web of Science and 103 Scopus entries. Following title, abstract, and full text screening, 99 records were excluded as out of scope (as they did not include any biodiversity component assessed or analyzed using GEDI data), leaving 26 studies that met all inclusion criteria. Three additional papers identified through the Zotero GEDI Peer Reviewed Publications Group were included, resulting in a final dataset of 29 studies. The number of studies published each year shows a clear upward trend from 2019 to 2025 (figure 2(B)). The presence of studies already in the first and second year following GEDI's launch

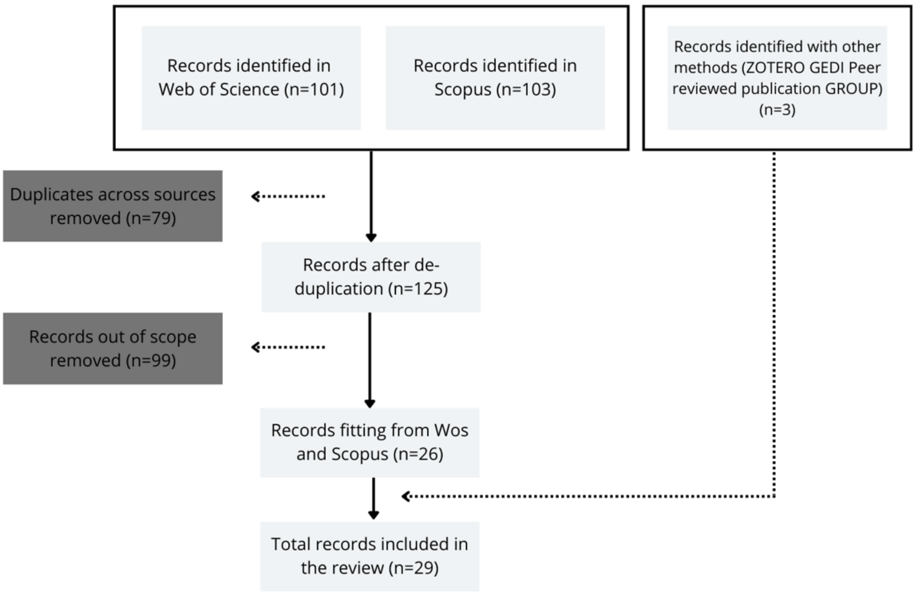

Figure 1. PRISMA style flow diagram summarizing the search and selection process for the reviewed studies. A total of 101 records were retrieved from Web of Science and 103 from Scopus, with 79 duplicates removed, resulting in 125 unique records. After screening for relevance, 99 records were excluded as out of scope, as they did not include any biodiversity component assessed or analyzed using GEDI data. Twenty six studies met all inclusion criteria from WoS and Scopus, and 3 additional papers identified through the Zotero GEDI Peer Reviewed Publications Group were included, giving a final set of 29 studies analyzed in this review.

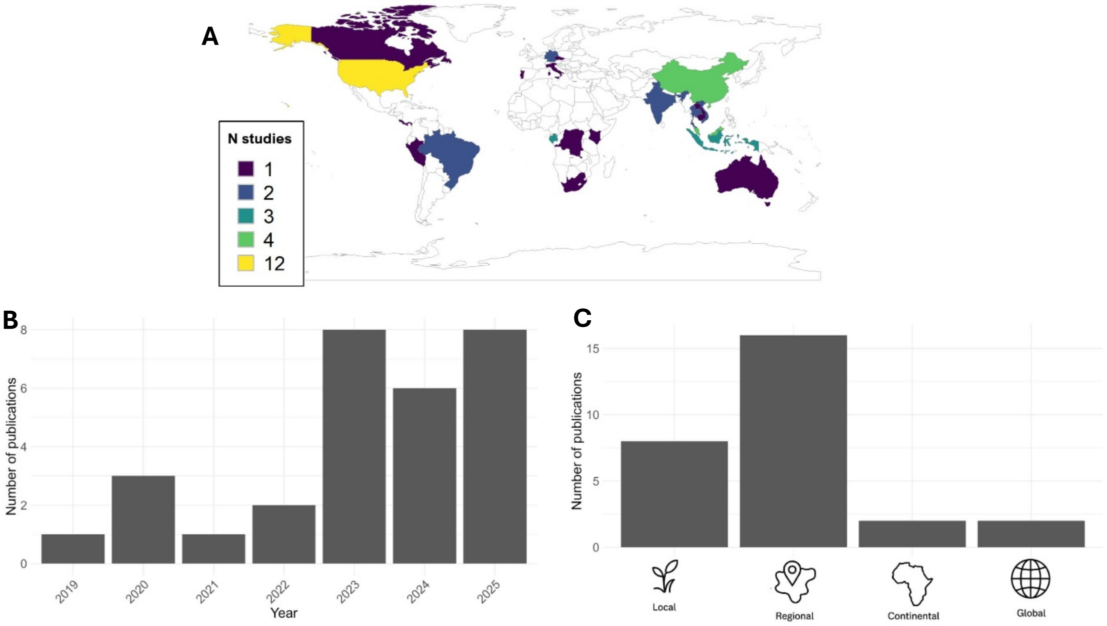

Figure 2. Overview of the 29 studies included in this review. (A) Geographic distribution of study areas across 23 countries. To highlight that several studies span multiple countries. (B) Number of GEDI based biodiversity studies published per year (2019–2025). Publications increase steadily over time, reflecting growing interest and improved data availability (* because the literature search ended on 21 October 2025, the final count for 2025 may be higher). Early studies (2019–2020) primarily relied on simulated GEDI data. (C) Spatial extent of analyses, showing a predominance of regional scale studies, with fewer applications at local, continental, or global scales.

is primarily due to the use of GEDI data simulated from ALS data, rather than actual GEDI observations (see section 3). Literature was assessed up through 21 October 2025.

In total, the use of GEDI data for biodiversity assessment has been tested in 25 different countries included in this review (figure 2(A)). The United States emerged as the country with the highest number of study areas, with 12 publications. Far behind, but still notable, are China and Malaysia with 4 publications; Gabon, Indonesia and Brunei with 3 publications each. Some publications (Brodie *et al* 2023, Landmann *et al* 2023, Torresani *et al* 2023, Burns *et al* 2025) used GEDI data for biodiversity assessment across multiple countries. When considering the continental distribution of study areas, Asia accounted for 42%, North America for 23%, Africa for 11%, South America and Europe for 9% and Oceania for 2% of the total reviewed studies. Only 4% of the studies were carried out at global scale.

A clear majority of the reviewed studies (17/29) were conducted at the regional scale (figure 2(C)) eight studies at the local scale while two at continental/global scale. This pattern reflects both GEDI's footprint geometry—well aligned with landscape scale heterogeneity—and the uneven availability of standardized biodiversity data: most field datasets occur at local/regional extents and pair readily with GEDI footprints, whereas harmonized biodiversity data at continental/global scales remain comparatively scarce and taxonomically uneven.

3. An ecosystem-oriented perspective on GEDI applications for biodiversity assessment

The vast majority of studies were conducted in natural or semi natural forests, highlighting GEDI's strong adoption in forest ecology research (figure 3). Studies range from tropical (Marselis *et al* 2020, Burns *et al* 2025), temperate (Schneider *et al* 2020, Barry *et al* 2024), alpine (Torresani *et al* 2023), and savanna (Rex *et al* 2025) forests across various continents, and include multi-biome studies across multiple forest types (Hakkenberg *et al* 2023a). Across these forest-focused applications, GEDI derived structural metrics often provided useful explanatory power for biodiversity patterns (Marselis *et al* 2019, Schneider *et al* 2020), but the strength of their effects and overall model performance varied substantially among studies (Ren *et al* 2023, Vogeler *et al* 2023, Marcilio-Silva *et al* 2025). This variability is expected: structural and biological diversity are often interrelated in forests, where vertical and horizontal heterogeneity—captured by lidar—can co-vary with species diversity across taxa (Goetz *et al* 2007, Torresani *et al* 2023, Hakkenberg *et al* 2023a). At the same time, several studies reported modest predictive strength (Bührs *et al* 2024, Barry *et al* 2024, Elliott *et al* 2024), reflecting both ecological complexity and the challenge of linking footprint level structure to field biodiversity observations, particularly when plot sizes, species abundances, and spatial heterogeneity introduce uncertainty. GEDI's waveform metrics are generally effective at describing vertical canopy structure when vegetation is sufficiently tall and distinct from the ground surface. However, in ecosystems with short stature vegetation or pronounced horizontal heterogeneity—such as savannas, shrublands, or highly fragmented forest—the main limitations arise from: (i) the limited ability of waveform measurements to resolve fine scale vertical structure, particularly in short stature vegetation where canopy and ground signals are less distinct; and (ii) the mission's sparse sampling density and footprint spacing, which restrict the representation of fine scale horizontal structural variation. As a result, 25 m footprints may overlook small or discontinuous vegetation patches, weakening structure–biodiversity relationships (Rex *et al* 2025). A smaller proportion of studies applied GEDI to mixed ecosystems, where multiple vegetation types co-occur within the same landscape mosaic. Because this evidence base is limited, broad generalizations are premature; nonetheless, the available studies indicate that GEDI derived structural metrics can—albeit with variable effectiveness—capture biodiversity patterns beyond structurally homogeneous forests, including across ecotones and heterogeneous mosaics integrating forests, shrublands, and grasslands (Burns *et al* 2020, Ilangakoon *et al* 2021, Martins *et al* 2024, Xu *et al* 2024). Only a handful of studies have extended GEDI applications into urban contexts, either in urban forests or broader metropolitan areas. In cities, GEDI's structural metrics have been combined with other high resolution datasets to enable detailed biodiversity assessments, from tree level classification to species distribution modeling (SDM) (Bührs *et al* 2024, Marcilio-Silva *et al* 2025, Wang *et al* 2025). These studies highlight not only the feasibility of mapping urban tree species when GEDI is fused with fine resolution optical data (Wang *et al* 2025), but also the potential to identify biodiversity hotspots within fragmented green spaces, such as revitalized industrial sites or remnant brownfields (Bührs *et al* 2024).

4. Biodiversity dimensions and metrics

The reviewed publications were almost evenly split between vegetation and animal-focused studies (figure 4). Within vegetation, the overwhelming majority (13 studies) concentrated on trees (Marselis *et al* 2022, Ren *et al* 2023, Torresani *et al* 2023), while only a few extended analyses to vascular plants (Hakkenberg *et al* 2023a) or shrubs (Ilangakoon *et al* 2021). As previously discussed, this strong emphasis on trees likely reflects both the nature of GEDI measurements—optimized to characterize overstory canopy structure at 25 m footprint scale by contrast, lower stature vegetation types are less accurately characterized because of geolocational imprecision, signal saturation in the upper canopy, as well as spatial and vertical resolution constraints for detecting small volume, low stature individuals in shrubs or herbaceous layers (Moudrý *et al* 2024b). Animal focused

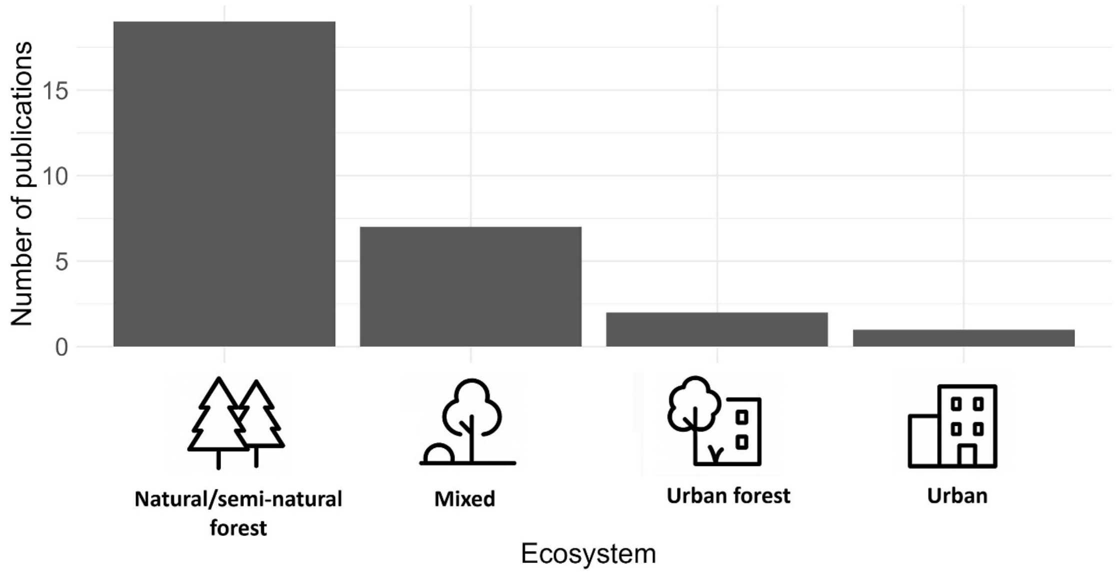

Figure 3. Proportion of studies using GEDI for biodiversity assessment across different ecosystem types. Most studies ($n = 19$) focused on forested ecosystems while a smaller share focused on mixed ecosystems ($n = 7$ where a variety of vegetation types within the same study co-occur), urban forests ($n = 2$) and general urban areas ($n = 1$).

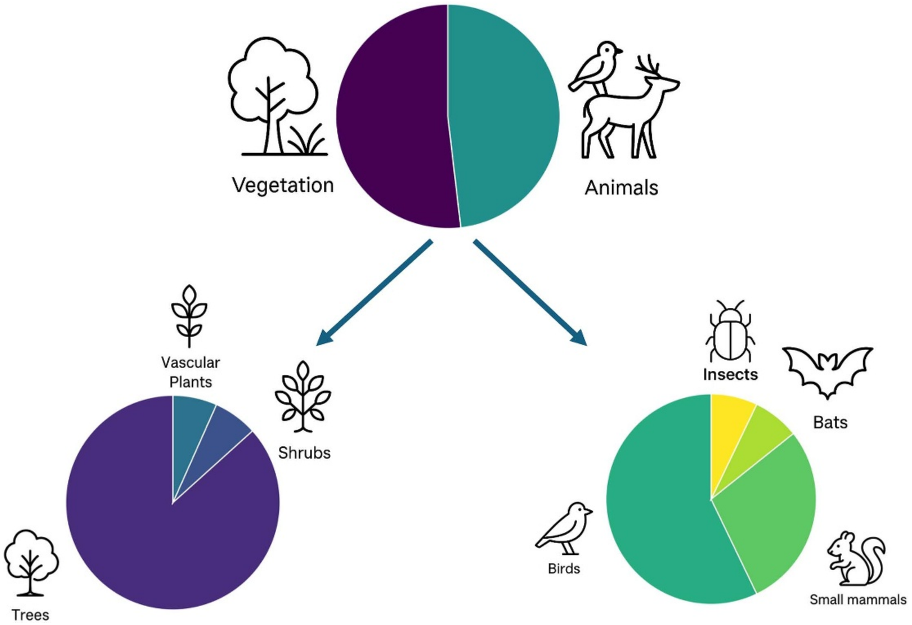

Figure 4. A bit more than half of the reviewed studies focused on vegetation biodiversity and the rest on animal biodiversity. Within vegetation studies, most ($n = 13$) focused on tree biodiversity, with a smaller proportion addressing vascular plants ($n = 1$) and shrubs ($n = 1$). Among animal studies, the majority focused on birds ($n = 8$), followed by terrestrial mammals ($n = 5$) and bats and insects (both $n = 1$). Only one study focused on both birds and mammals simultaneously.

studies were dominated by birds (8 studies), with GEDI used as a proxy to model richness, distributions, or habitat suitability (Burns *et al* 2020, Vogeler *et al* 2023, Elliott *et al* 2024, Xu *et al* 2024). Birds are particularly well represented because their ecology is strongly tied to vertical habitat structure, and because standardized occurrence datasets are widely available from surveys and citizen science. This combination—tight ecological links to canopy heterogeneity and abundant monitoring data—makes birds an ideal group for testing GEDI's contribution to biodiversity models. Terrestrial mammals accounted for a smaller share (5 studies), typically relying on more spatially constrained sources such as camera traps to link forest structure with species distributions, density or occupancy (Smith *et al* 2022, Brodie *et al* 2023, Killion *et al* 2023, Barry *et al* 2024, Burns *et al* 2025). Both types of datasets, camera traps and citizen science observations, are valuable but, like all biodiversity data, are subject to taxonomic and methodological

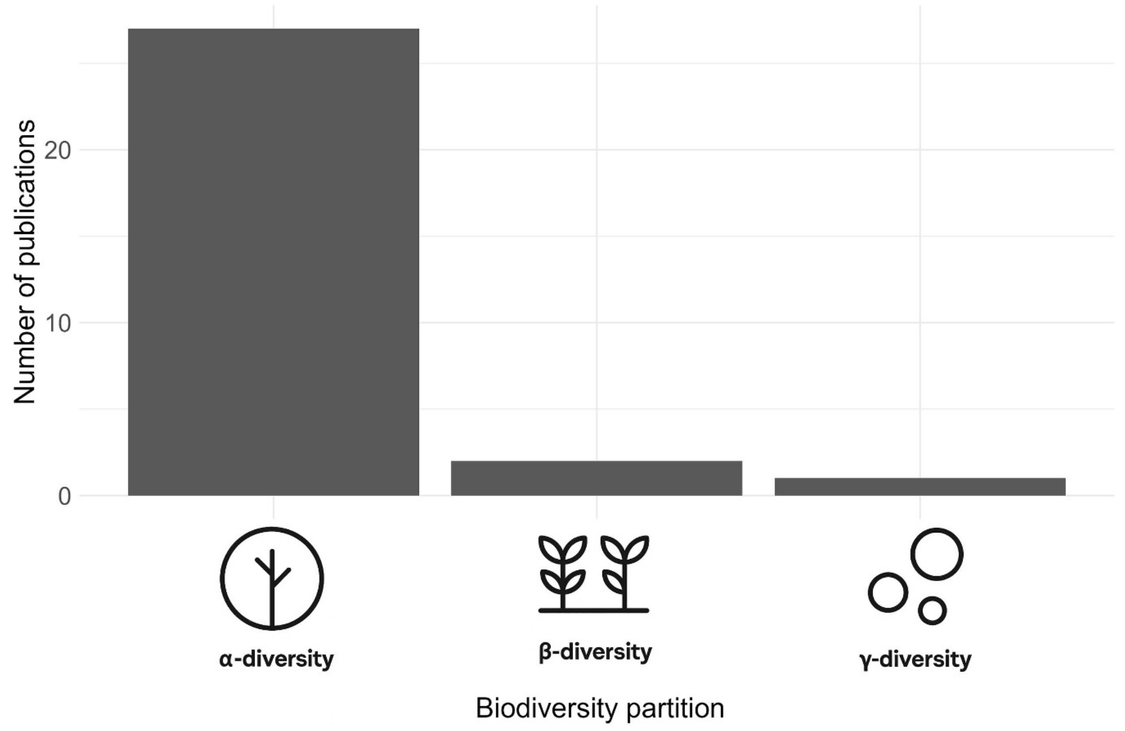

Figure 5. Distribution of biodiversity dimensions assessed across the reviewed studies. Most studies focused on alpha level information, including both community level diversity metrics (e.g. richness, Shannon's (H) and species specific habitat or occurrence models, which operate at the same site level scale. Only two studies examined beta diversity, and a single study included gamma diversity.

biases. For example, camera traps may underrepresent arboreal species or capture only a subset of the fauna, while citizen science data can be influenced by uneven sampling effort and observer bias. These limitations can complicate their integration with canopy focused lidar metrics; nevertheless, they represent a rapidly growing and increasingly important source of biodiversity information for large scale ecological analyses. Only one study focused on both birds and mammals simultaneously (Brodie *et al* 2023). Bats and insects were each addressed only once (Landmann *et al* 2023, Martins *et al* 2024).

Most reviewed studies focused on alpha level information, while beta diversity received far less attention. Only a few studies addressed beta diversity or functional diversity (Schneider *et al* 2020), and only Hakkenberg *et al* (2023a) also considered both beta and gamma diversity (figure 5). This imbalance reflects the relative ease of linking GEDI's footprint level structure to site specific richness compared to capturing spatial turnover or regional scale diversity. Alpha diversity is the most frequently analyzed dimension, as it can be directly linked to vegetation structure derived from GEDI. However, owing to geolocation error and GEDI's sparse sampling, which may render large distances between a field observation and the most proximate GEDI footprint, most studies rely on aggregated or fused products. Examples are provided by continuous gridded CHMs or structure maps, where structure metrics are first modeled by integrating GEDI footprints with optical, SAR or environmental data, rather than using individual footprints (Hakkenberg *et al* 2023b, de Conto *et al* 2026). These spatially continuous, derived products capture vertical and horizontal heterogeneity, which often correlates with local species richness or other diversity indices. By contrast, beta and gamma diversity require capturing spatial turnover and regional richness across heterogeneous landscapes, which is more challenging with GEDI's sampling design. The sparse, discontinuous footprints limit its ability to represent compositional differences between neighboring sites or to scale consistently across broad regions. Moreover, many available biodiversity datasets, such as forest inventories or plot networks, are themselves structured around alpha level metrics, reinforcing the focus on local diversity. Addressing beta and gamma diversity typically requires integrating GEDI with wall to wall predictors—such as satellite image or climatic layers—to capture spatial turnover across landscapes. Importantly, most alpha diversity studies also rely on such complementary datasets, as very few analyses use GEDI footprints alone without aggregation or interpolation. However, the dependence on wall to wall products becomes even more critical for beta and

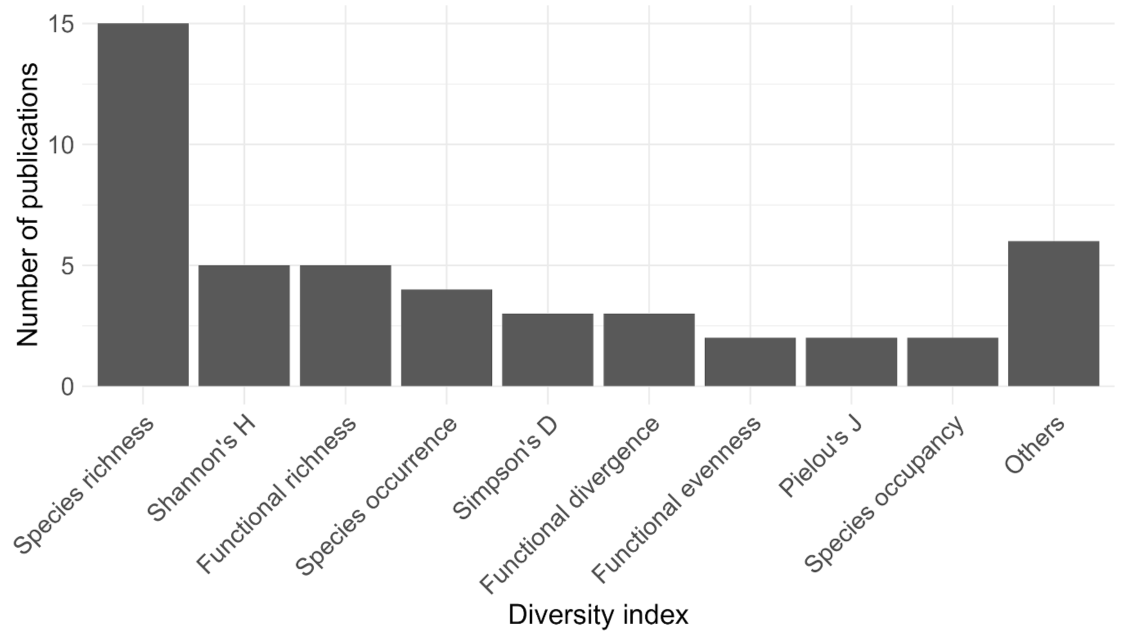

Figure 6. Distribution of *in-situ* biodiversity indices used across studies applying GEDI data.

gamma diversity, where capturing spatial gradients is essential (Burns *et al* 2025).

When examining the diversity indices applied—particularly in the context of alpha diversity—species richness (i.e. the number of species within a given area) clearly dominates (figure 6). This is not surprising given richness is conceptually simple and more widely available in field datasets. For vegetation, several studies have documented strong relationships between species richness and canopy attributes such as height, foliage profile, and vertical heterogeneity (Marselis *et al* 2022, Ren *et al* 2023). What makes richness attractive is that it can be scaled from local plots to broad gradients, serving both as a baseline biodiversity measure and as a benchmark against which more complex indices can be tested. For animal focused research, species richness has also been used, but requires other considerations including observation effort and the motility of individuals with habitat space. Studies mapping birds and mammals highlight that richness is shaped not only by forest structure but also by species motility, trophic interactions, habitat specificity, and observation-related biases (Elliott *et al* 2024, Burns *et al* 2025). This makes GEDI's contribution to animal richness models less direct: structural metrics add value, but reliable predictions typically require inclusion of climate, geomorphology or land cover/land use covariates.

By contrast, Shannon's H, one of the most widely applied indices in ecological research, that captures both richness and the relative abundance of species within a community, was used far less frequently in GEDI studies, and when it appeared, it was confined to vegetation-focused analyses of tree communities (Marselis *et al* 2019, Ren *et al* 2023, Torresani *et al* 2023, Rex *et al* 2025, Zhang *et al* 2025).

Species occurrence utilized predominantly in animal-focused studies. Its appeal lies in the scalability of presence data, which are widely available for birds owing to monitoring schemes and citizen science initiatives (Burns *et al* 2020, Smith *et al* 2022, Vogeler *et al* 2023, Elliott *et al* 2024). For mammals, however, occurrence data were more limited, often relying on localized methods such as camera traps (Burns *et al* 2025). The need to integrate species abundances across a 25 m GEDI footprint can blur signals from field plots, especially in structurally and compositionally heterogeneous ecosystems, thereby reducing the sensitivity of Shannon's H. Similar concerns have been raised in optical remote sensing, where abundance-weighted indices can be weakened by scale mismatches between field plots and pixel size (Gamon *et al* 2020, Moudrý *et al* 2023, Torresani *et al* 2025).

Other indices appeared only sporadically but offer important insights into what GEDI could contribute beyond richness. Functional evenness and related indices such as divergence, redundancy, and dispersion were tested in a handful of cases, often with encouraging results (Ilangakoon *et al* 2021, Brodie *et al* 2023, Xu *et al* 2024). Simpson's D and Pielou's J, both measures of evenness, were also applied occasionally (Ren *et al* 2023, Rex *et al* 2025), likely because they are even more sensitive than Shannon's H to abundance estimation and scale mismatches. A similar point applies to phylogenetic diversity, used in only one study so far (Brodie *et al* 2023), which points to opportunities but also to the current scarcity of field datasets that would enable linking GEDI's structure to evolutionary relationships. Species occupancy, implemented via hierarchical frameworks, was tested in two studies—one on mammals and one on bats (Killion *et al* 2023, Martins *et al* 2024)—showing that GEDI derived structure can be integrated into models that explicitly account for detectability and observation uncertainty, with generally moderate gains.

Overall, most studies evaluated multiple biodiversity indices simultaneously, treating richness, occurrence, and—in some cases—functional measures as complementary rather than mutually exclusive indicators (Burns *et al* 2020, 2025, Marselis *et al* 2020, 2022, Bührs *et al* 2024). This reflects both the recognition that no single metric can capture the full complexity of biodiversity and the practical constraints imposed by the type and quality of field data available.

5. GEDI data characteristics and application modes

Most studies now rely on actual GEDI observations rather than simulations, underscoring how quickly the mission has become a core resource for biodiversity research (figure 7(A)). Before data were available, simulated GEDI waveforms offered a critical testing ground. By degrading high resolution ALS data to match GEDI's footprint size and pulse characteristics, early work explored the extent to which structural metrics such as relative height (RH), plant area index (PAI), or FHD could serve as proxies for biodiversity (Hancock *et al* 2019). These simulations (Marselis *et al* 2019, 2020, Burns *et al* 2020, Schneider *et al* 2020, Rex *et al* 2025) were not just methodological exercises: they helped identify where GEDI would be most informative, and where its sampling geometry and spatial spacing would impose limits. At the same time, it is worth mentioning that real GEDI data introduce additional sources of uncertainty—such as geolocation error and sensor noise—that are largely absent from simulated datasets and may affect model performance at local habitat or diversity scales. Although real GEDI data offer global, repeatable coverage and temporal depth, simulated datasets remain useful for controlled experiments and for regions without GEDI observations. Crucially, both real and simulated GEDI data share the same fundamental sampling and scale constraints.

Only about one third of the reviewed studies relied exclusively on GEDI derived variables (figure 7(B)) (Marselis *et al* 2019, 2020, Schneider *et al* 2020, Brodie *et al* 2023, Hakkenberg *et al* 2023a, Xu *et al* 2024), underlining both the mission's standalone potential and its frequent augmentation with complementary information. Across these GEDI only applications, the strength of the structure–biodiversity relationships varied substantially among taxa, regions, and modeling strategies, which makes direct comparison difficult. By contrast, the remaining studies integrated GEDI with ancillary datasets, and these integrations can be broadly grouped into two distinct modes. The first, which we refer to as fusion for structure, uses GEDI footprints as calibration data for producing wall to wall maps of vegetation structure—typically canopy height, PAI, FHD, or related metrics—by combining GEDI with optical, radar, or environmental predictors. These fused structural products subsequently serve as inputs to biodiversity analyses (Bodh *et al* 2023, Torresani *et al* 2023, Vogeler *et al* 2023, Burns *et al* 2025). The second mode, fusion for biodiversity, incorporates GEDI metrics directly into species-specific or diversity models alongside climate, land cover, phenology, or optical and radar-derived predictors. In these studies, GEDI represents one component within a multivariate predictor stack aimed at estimating richness, occurrence, occupancy, or habitat suitability (Burns *et al* 2020, Ren *et al* 2023, Elliott *et al* 2024, Martins *et al* 2024). Across both fusion modes, optical remote sensing provided the most common source of complementary information. Sentinel-2 contributed fine spatial and spectral detail (Ren *et al* 2023, Martins *et al* 2024, Quinn *et al* 2024, Marcilio-Silva *et al* 2025, Rex *et al* 2025), Landsat time series supplied multi decadal disturbance and phenological context (Bodh *et al* 2023, Vogeler *et al* 2023, Barry *et al* 2024, Burns *et al* 2025), and MODIS added high frequency phenological metrics (Burns *et al* 2020, Killion *et al* 2023, Satapathy and Dutta 2025). Additional optical products—including hyperspectral imagery from Chinese GF-5 and multispectral data from GF-1 and GF-6 satellites—proved particularly effective in urban tree-classification settings (Wang *et al* 2025, Zhang *et al* 2025). Radar—especially Sentinel-1—was frequently incorporated to capture canopy moisture, disturbance, and texture, complementing GEDI's vertical detail (Vogeler *et al* 2023, Barry *et al* 2024, Martins *et al* 2024). Radar missions, such as JAXA's Phased Array L-band Synthetic Aperture Radar (PALSAR) on ALOS/ALOS-2/ALOS-4, the recent NASA-ISRO Synthetic Aperture Radar (NISAR), and ESA BIOMASS and the future ROSE-L, with their longer wavelengths and enhanced sensitivity to canopy volume and vertical structure, might offer promising opportunities to mitigate this issue and improve the 3D structural representation in fusion frameworks (Goetz and Dubayah 2011). Beyond spectral and structural inputs, several studies incorporated climate, land cover, and topography (Vogeler *et al* 2023, Bührs *et al* 2024, Barry *et al* 2024, Elliott *et al* 2024, Rex *et al* 2025). More experimental predictors—proximity to streams, roads, or coastlines (Burns *et al* 2020), moon phase for nocturnal activity (Martins *et al* 2024), or proxies for anthropogenic pressures (Brodie *et al* 2023) broadened

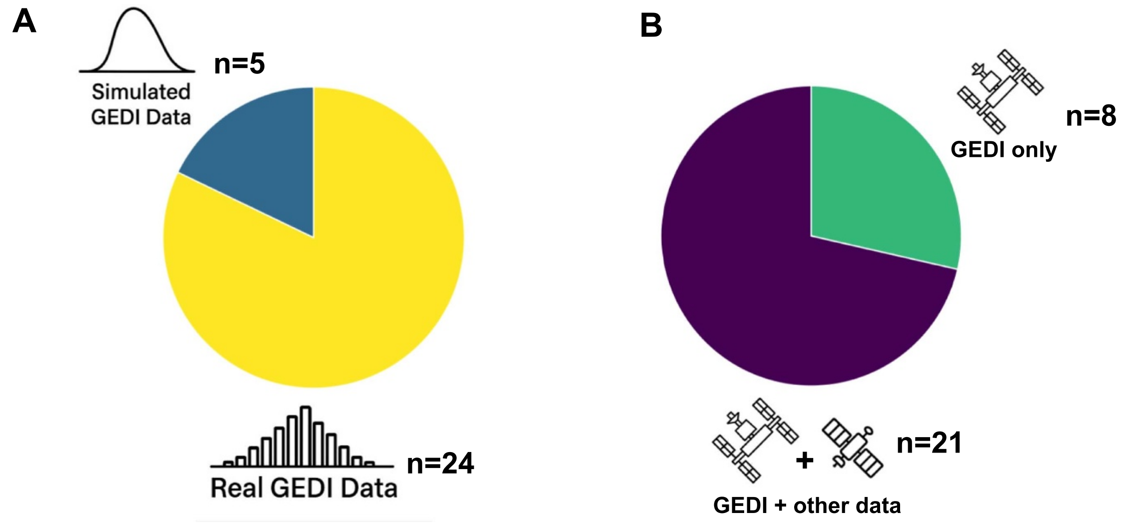

Figure 7. (A) Proportion of studies using actual GEDI observations versus simulated GEDI data ($n = 24$ real GEDI data and $n = 5$ simulated) and (B) proportion of studies using GEDI in combination with other data sources versus GEDI-only approaches ($n = 21$ in combination and $n = 8$ GEDI only).

ecological interpretation but did not always yield stronger predictions. The most robust results came from combinations that paired GEDI's unique structural detail with predictors targeting complementary ecological gradients (e.g. phenology, climate). However, it is difficult to determine whether GEDI metrics are truly essential predictors or simply one component among others, unless models explicitly compare different data source combinations, which is, however, rare (Marselis *et al* 2022). Some studies have addressed this by contrasting models built with individual versus combined datasets (Vogeler *et al* 2023). In other cases, the inclusion of many partially redundant predictors—each individually ecologically justified—made it harder to isolate GEDI's unique contribution to model performance. Importantly, it is commonly emphasized in the literature that data fusion should not be driven by availability alone (Cavender-Bares *et al* 2022). In this sense, GEDI data are best understood not as a one-size-fits-all predictor, but rather as a structural cornerstone whose value is maximized within carefully designed, ecologically informed modeling frameworks.

6. Analytical approaches and analyses

The reviewed studies can be grouped into five main analytical families, each reflecting distinct strategies for linking GEDI structural information with aspects of biodiversity (table 2). These families differ not only in the statistical tools employed but also in their conceptual goals—ranging from direct explanatory models of structure–diversity relationships to predictive frameworks for habitat suitability and community composition. Structure–diversity approaches remain the most common, capitalizing on the intuitive expectation that vertical and horizontal canopy attributes (e.g. RH, FHD, PAI, canopy heterogeneity) are associated with species diversity. A special case within this group is the height variation hypothesis (Torresani *et al* 2020, Tamburlin *et al* 2021, Rahmsdorf *et al* 2025), explicitly tested by Torresani *et al* (2023), which treats canopy height heterogeneity quantified through different heterogeneity indices (Thouverai *et al* 2022, Rocchini *et al* 2024) as a mechanistic driver of tree diversity. This illustrates how GEDI can contribute not only as a statistical predictor but also as a tool for testing ecological theory. Species–habitat models build on the same principle underlying structure–diversity analyses: that canopy structure measured by GEDI reflects habitat attributes relevant to species distributions. These studies integrate GEDI-derived metrics into SDMs, occupancy frameworks, or demographic models to predict animal richness, occurrence, or habitat suitability (Burns *et al* 2020, Vogeler *et al* 2023, Barry *et al* 2024, Elliott *et al* 2024, Martins *et al* 2024). A recurrent finding is that GEDI structure metrics add intuitive explanatory power—particularly for birds, which are closely tied to canopy structure—but are generally insufficient on their own. Successful applications balance structural predictors with climate, land cover, or topography, while overfitting remains a risk when too many predictors are included (Burns *et al* 2025). A smaller group of studies uses GEDI metrics as proxies for functional traits describing vegetation architecture. These analyses quantify functional richness, divergence, evenness, or redundancy (Schneider *et al* 2020, Ilangakoon *et al* 2021, Satapathy and Dutta 2025). Here, GEDI is valued for capturing vertical niche space rather than taxonomic

Table 2. Standardized analytical approaches used across the reviewed GEDI biodiversity studies, grouped into five major classes.

Class	Definition	Papers in this review
Structure–diversity (incl. HVH)	Regression or correlation based approaches that directly relate GEDI structural metrics to biodiversity information. Includes classical regression, GLM/GLMM, Poisson models, and explicit tests of the Height Variation Hypothesis (HVH).	Marselis *et al* (2019, 2020, 2022), Ren *et al* (2023), Torresani *et al* (2023), Hakkenberg *et al* (2023a), Marcilio-Silva *et al* (2025), Rex *et al* (2025), Xu *et al* (2025), Zhang *et al* (2025)
Species–habitat models (SDM/occupancy/demography)	Models predicting species occurrence, encounter rates, habitat suitability, or demographic parameters from GEDI and other predictors. Includes SDMs, Random Forest, ensemble ML, hierarchical occupancy models, and GLMMs for density or survival.	Burns *et al* (2020), Smith *et al* (2022), Killion *et al* (2023), Landmann *et al* (2023), Vogeler *et al* (2023), Bührs *et al* (2024), Barry *et al* (2024), Elliott *et al* (2024), Martins *et al* (2024), Quinn *et al* (2024), Xu *et al* (2024), Prajzlerová *et al* (2025)
Functional diversity (TPD-based)	Trait-based models using GEDI-derived canopy structure as functional traits. Includes TPD frameworks, PCA, and indices such as FRic, FEve, FDiv, FDis, and FRed.	Schneider *et al* (2020), Ilangakoon *et al* (2021), Satapathy and Dutta (2025)
Community/classification models	Approaches that classify species communities, vegetation types, or forest assemblages using GEDI + ancillary data. Includes ordination (e.g. TWINSPAN), clustering, and ML classifiers (e.g. Random Forest).	Bodh *et al* (2023), Wang *et al* (2025)
Spatial statistics (hotspots, kriging, beta–gamma)	Geostatistical or spatially explicit approaches for analyzing biodiversity patterns. Includes kriging/interpolation of GEDI structure, hotspot mapping, dissimilarity-based beta–gamma diversity, and mixed spatial models.	Brodie *et al* (2023), Hakkenberg *et al* (2023a)

identity. Community classification approaches (Bodh *et al* 2023, Wang *et al* 2025) show yet another dimension, using GEDI with spectral and ancillary data to distinguish species or community types. Here the emphasis shifts from assessing statistical associations of structure metrics with diversity indices to mapping community level composition directly. Such studies demonstrate that GEDI can inform biodiversity science not just through proxies but also by supporting taxonomic classification when integrated with rich ancillary datasets. Finally, spatial statistical frameworks (Brodie *et al* 2023, Hakkenberg *et al* 2023a) illustrate how GEDI can be embedded into landscape scale models. By combining footprints with field data, kriging, or mixed effects approaches, these studies explore scale dependence and spatial turnover. Unlike other families, which emphasize predictor integration, this group takes advantage of GEDI's spatial sampling design itself to quantify biodiversity patterns across scales. Taken together, these analytical families are complementary rather than competing. Structure–diversity and species–habitat models are closest to ecological applications, functional and community classification studies expand the range of biodiversity dimensions considered, fusion mapping addresses sampling limitations, and spatial statistics tackle scale dependence. The diversity of approaches reflects both the flexibility of GEDI data and the challenges of aligning a footprint based sensor with heterogeneous biodiversity metrics.

7. Current limitations and future perspectives

Although applications of GEDI to biodiversity assessment are rapidly expanding, several uncertainties still limit the robustness and generalizability of results. These arise both from intrinsic mission characteristics and from methodological and ecological challenges, but they also point toward opportunities for future work. GEDI's sampling design provides billions of globally distributed observations, yet footprints are spatially discontinuous and confined to latitudes between 51.6° N–S (Dubayah *et al* 2022).

A further challenge is the potential misalignment between GEDI 25 m diameter footprints and field plots, the latter of which are typically smaller or irregularly shaped. Even when overlap appears, GEDI's ∼10 m geolocation error (Roy *et al* 2021, Wang *et al* 2024, Pascual *et al* 2025) reduces confidence in co-location, especially in heterogeneous terrain where small shifts alter canopy signals, illustrating how footprint centers can vary considerably around their nominal location. As noted by different studies (Kashongwe *et al* 2023, Hakkenberg *et al* 2023a), GEDI's transect sampling design rarely coincides with plots, making direct calibration difficult if the plot sampling is not specifically designed for that purpose. In recent years, several studies have developed algorithms to mitigate this source of error (Schleich *et al* 2023, Wang *et al* 2025). Nevertheless, possible solutions include the approach proposed by Cooley *et al* (2024), which suggests using larger field plots of about 45 m in diameter to better encompass the GEDI footprint and account for geolocation errors, or even larger plots, where large stem-mapped plots ($\geqslant$1 ha) reduce edge and geolocation mismatch, and may be subdivided into GEDI-footprint units (Duncanson *et al* 2022). This practice aligns with CEOS LPV best-practice guidance that recommends precisely geolocated 1 ha, stem-mapped plots, ideally colocated with ALS data, to minimize spatial uncertainty in biomass validation (Duncanson *et al* 2021). These approaches can reduce footprint–plot mismatches and edge effects, but they require careful plot placement and screening to ensure that the enlarged plot area represents a single, internally homogeneous vegetation type; otherwise, spatial averaging may mix multiple stand conditions and obscure structure–biodiversity relationship.

Another limitation, briefly discussed in section 3, is that the performance of GEDI structural metrics varies across ecosystems. In open or low stature systems, ground detection is generally reliable, but sparse sampling and limited vertical contrast reduce sensitivity to fine scale heterogeneity, whereas in dense forests (e.g. tropical), signal attenuation and waveform saturation can complicate canopy–ground separation (Cho *et al* 2025, Rex *et al* 2025).

Beyond sampling and geolocation issues, a further limitation arises from the heterogeneous ways in which GEDI data have been processed across studies, which complicates comparison and may influence ecological conclusions. Among studies that used actual GEDI observations (rather than simulations), only five studies relied directly on lidar measurements. Typically, they aggregated metrics derived from individual GEDI footprints (i.e. Level 2 data) into larger grid cells or buffers (Hakkenberg *et al* 2023b, Xu *et al* 2024), or used mission-derived gridded products (i.e. Level 3 data) (Prajzlerová *et al* 2025). Directly measured GEDI data provide relatively accurate estimates of vegetation structure, but biodiversity studies are often limited by discrete GEDI sampling. Indeed, eleven studies required spatially continuous vegetation-structure data at relatively fine resolution. To obtain these, they used interpolation approaches (Brodie *et al* 2023, Ren *et al* 2023), engaged in fusion-for-structure workflows that predict wall to wall canopy metrics using optical or radar predictors (Bodh *et al* 2023, Martins *et al* 2024), or relied on existing global predicted canopy-structure maps (Torresani *et al* 2023). Locally derived structure predictions (produced specifically for individual study areas) are generally more accurate than global predicted maps (Moudrý *et al* 2024a). However, comparing ecological results across studies that rely on such heterogeneous approaches can be misleading. Although predicted vegetation-structure metrics offer higher spatial detail, their fusion- or model-based uncertainties may propagate into biodiversity analyses, influencing estimated species–environment relationships (Moudrý *et al* 2024a). Much of this methodological diversity stems from the fact that, at the time many studies were conducted, neither standardized GEDI gridded products nor globally harmonized canopy structure maps were readily available. Future biodiversity assessments will likely shift toward using standardized, validated GEDI-based structure products—including both mission-derived L3 layers and Fusion-for-Structure maps—which should improve comparability across regions, ecosystems, and taxa.

Validation data themselves add constraints. Most studies emphasize alpha diversity—dominated by species richness—while Shannon's H, Simpson's D, functional or phylogenetic metrics, and especially beta and gamma diversity remain underexplored, with only few exceptions (Brodie *et al* 2023, Hakkenberg *et al* 2023a). Taxonomic coverage is also narrow, focusing mainly on trees and birds. Analytical choices also strongly influence outcomes: the scale of aggregation, choice of algorithm, treatment of spatial autocorrelation, and whether uncertainties (geolocation, fusion map errors) are propagated. Transparent reporting of these steps, and systematic benchmarking across models, improve comparability and robustness. Additionally, the growing volume and complexity of GEDI and fusion datasets underscore the need for powerful data storage and high performance processing tools to ensure reproducible and scalable analyses.

Looking ahead, several avenues offer the potential to overcome current limitations and expand GEDI's role in biodiversity monitoring and science. A first priority is cross mission synergy: integration with other satellite laser altimeters such as ICESat-2 (Abdalati *et al* 2010) or complementary sensors such as NISAR (Xaypraseuth *et al* 2015), BIOMASS (Quegan *et al* 2019), and forthcoming NASA missions could mitigate sampling gaps and provide additional structural and biophysical parameters. Particularly promising is NASA's Earth Dynamics Geodetic Explorer (EDGE) mission, a swath-mapping satellite lidar for joint mapping of

3D canopy structure and surface topography which was selected within NASA's Earth Systems Explorer (ESE) program for launch in 2030 (Garvin *et al* 2026). EDGE will deliver continuous swath lidar measurements of canopy height, foliage profiles and structural complexity with improved coverage, resolution, geolocation and targeting capabilities compared to GEDI, enabling biodiversity mapping at unprecedented scales. Similarly, the upcoming surface topography and vegetation mission (Donnellan *et al* 2024) is expected to provide continuity and long term monitoring capabilities. Integration with field data will remain essential in future studies. Expansion of standardized biodiversity monitoring networks (e.g. NEON, ICP Forests, ForestGEO) and improved protocols for co-locating plots with footprints will enhance calibration and validation (Hakkenberg and Goetz 2021). Moreover, extending GEDI based approaches into urban and non forest ecosystems (Marcilio-Silva *et al* 2025, Wang *et al* 2025) offers opportunities to connect forest structure with biodiversity in landscapes of high societal relevance.

Conceptual advances are also needed. As previously stressed, most applications remain focused on alpha diversity, yet extending analyses to beta and gamma diversity (Brodie *et al* 2023, Hakkenberg *et al* 2023a) would better capture spatial turnover and regional gradients, potentially through the use of advanced machine learning techniques such as ensemble models or deep learning architectures, which can handle non linear relationships and integrate diverse environmental predictors. The integration of functional and phylogenetic metrics could further align GEDI based studies with contemporary biodiversity theory. In parallel, the development of global, ready to use structure datasets in public cloud systems (Burns *et al* 2024), (available via Google Earth Engine) may lower barriers for biodiversity researchers less experienced in remote sensing, broadening the user base and accelerating ecological applications.

Beyond academic applications, GEDI also holds strong potential for biodiversity conservation, such as detecting forest disturbance around protected areas or distinguishing habitats that differ in vertical structure but appear spectrally similar—key capabilities for supporting ongoing global efforts toward fine scale habitat mapping.

Ultimately, the long term impact of GEDI will depend on ensuring continuity beyond its current mission window, while building the methodological and ecological frameworks to integrate spaceborne lidar with other EO tools. If these opportunities are realized, GEDI and its successors could transform biodiversity monitoring by providing globally consistent, structurally explicit, and ecologically meaningful insights across scales.

8. Conclusions

This review shows that GEDI metrics have changed the landscape of biodiversity monitoring by providing globally consistent, structurally explicit observations that scale beyond the reach of airborne campaigns. The strongest results arise where GEDI metrics address a clearly articulated ecological mechanism—most commonly for alpha diversity of trees and, to a lesser extent, birds—while complementary optical, radar, topographic, and climatic predictors capture orthogonal gradients. By contrast, stacking many predictors without ecological rationale can dilute GEDI's contribution and obscure inference. Three strategic gaps remain: (i) scale and alignment: sparse, footprint based sampling, limited latitudinal coverage, and geolocation uncertainty complicate direct calibration with field plots and hamper transfer to beta and gamma diversity. (ii) uncertainty and validation: propagation of measurement and fusion map errors is still uncommon, and validation remains uneven across biomes, vegetation strata, and taxa. (iii) metric breadth: most studies remain anchored in richness; moving toward beta/gamma, functional, and phylogenetic dimensions will better exploit GEDI's 3D strengths while aligning with contemporary biodiversity theory.

We see clear opportunities to close these gaps. Methodologically, studies should (i) design fusion around hypotheses that pair GEDI's structure with complementary phenology, geomorphic and climate signals; (ii) propagate uncertainties (geolocation, sampling, fusion) into ecological models; and (iii) adopt biome specific filtering and aggregation strategies for footprint–plot matching. Empirically, expanding standardized monitoring networks and improving plot–footprint co location will strengthen validation, particularly outside temperate forests and beyond trees and birds. Programmatically, cross mission synergies promise improved coverage, repeatability, and structural detail, enabling routine biodiversity mapping across scales going forward. In sum, GEDI should be treated as a structural cornerstone in biodiversity models: powerful on its own for certain questions and indispensable when thoughtfully integrated with complementary data. With sustained continuity, rigorous uncertainty treatment, and theory driven fusion, spaceborne lidar can deliver ecologically meaningful, policy relevant biodiversity indicators from local landscapes to the globe.

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Data availability statement

No new data were created or analysed in this study.

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