

From Pixels to Species: A Review of Remote Sensing for Biodiversity Assessment

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Abstract: Remote sensing-based global biodiversity monitoring systems have transformed the field of conservation biology, enabling consistent assessment, monitoring, modelling, and reporting. These systems underpin sustainable management and informed decision-making, crucial for maintaining ecosystem health and resilience. Biodiversity monitoring is a complex process, involving multiple components that provide valuable insights into ecosystems. This review examines the significant contributions of remote sensing to biodiversity research, emphasising its potential for informing conservation decisions. Key components include biodiversity levels (genetic, species, and ecosystem), essential biodiversity variables, indicators, spatial and temporal scales, inventory, models, habitat assessment, evaluation of ecosystem services, vegetation health monitoring, and analysis of biogeochemical heterogeneity. Remote sensing through Earth Observations (EO) has revolutionised biodiversity research, offering unprecedented opportunities for monitoring ecological processes. EO technologies enable researchers to map biodiversity patterns, track changes, assess vegetation health, model species distribution and abundance, and evaluate ecosystem services. Integrating remote sensing and biodiversity science addresses pressing conservation questions, enabling researchers to develop effective monitoring strategies, improve biodiversity models, and enhance conservation outcomes.

Keywords: Biodiversity monitoring, Remote sensing, Earth observations, Conservation biology, Ecosystem services, Vegetation health

Conflicts of interest: None

Supporting agencies: None

Received 18.10.2024; Revised 13.02.2025; Accepted 23.02.2025

Cite This Article: Mallick, M. A. I. (2025). From Pixels to Species: A Review of Remote Sensing for Biodiversity Assessment. *Journal of Sustainability and Environmental Management*, 4(1), 40-61.

1. Introduction

Remote sensing-based global biodiversity monitoring systems have revolutionised the field of conservation biology, enabling consistent assessment, monitoring, modelling, and reporting of biodiversity patterns and trends (Mulatu et al., 2017; Cavender-Bares et al., 2022). These systems provide the foundation for sustainable management and informed decision-making, crucial for maintaining ecosystem health and resilience in the face of escalating environmental pressures (Blackmore & Plant, 2008). The importance of effective biodiversity monitoring cannot be overstated, as it underpins our ability to mitigate

biodiversity loss, protect ecosystem services, and preserve the natural heritage of our planet.

Biodiversity monitoring is a complex and multifaceted field, involving multiple components that provide valuable insights into ecosystems (Haase et al., 2018). At its core, biodiversity encompasses three primary levels: genetic, species, and ecosystem diversity (Rawat & Agarwal, 2015). Each of these levels offers unique perspectives on ecosystem functioning and health (Snelgrove et al., 2014). Genetic diversity, for instance, informs us about the variability within species, while species diversity sheds light on the richness and evenness of species composition (Hoban et al., 2022). Ecosystem diversity, meanwhile, highlights the range of habitats and ecological processes present within a given landscape (Peng et al., 2018).

To comprehensively understand biodiversity, researchers and conservationists rely on essential biodiversity variables (EBVs), indicators, spatial and temporal scales, inventories, models, habitat assessments, ecosystem services evaluations, vegetation health monitoring, and biogeochemical heterogeneity analyses (Jongman et al., 2017). EBVs, such as species population sizes and community composition, provide critical information on the status of ecosystems (Kissling et al., 2018). Indicators, such as the Index of Biological Integrity, provide simplified yet effective measures of biodiversity health (Brown & Williams, 2016). Spatial and temporal scales allow researchers to contextualise biodiversity patterns within specific ecosystems and timeframes (Pilowsky et al., 2022).

The integration of remote sensing and biodiversity science has transformed our understanding of ecological processes (Pettorelli et al., 2014). Remote sensing through Earth Observations (EO) enables researchers to map biodiversity patterns, track changes, assess vegetation health, model species distribution and abundance, and evaluate ecosystem services (Cord et al., 2017). EO technologies, including satellite, airborne, and ground-based sensors, provide unparalleled spatial and temporal coverage of ecosystems (Ustin & Middleton, 2021). Through these technologies, researchers can monitor biodiversity at local to global scales, facilitating the development of effective conservation strategies (Schmeller et al., 2017). Although progress has been made in remote sensing-based biodiversity monitoring, significant challenges remain. Data quality, availability, and integration issues persist, while scaling up monitoring efforts from local to global levels poses substantial logistical and analytical challenges (David et al., 2022). Moreover, the development of direct remote sensing approaches and techniques for quantifying biodiversity at community to species levels remains a pressing research priority (Reddy, 2021; Janga et al., 2023).

While the importance of remote sensing for biodiversity monitoring is well-established, there remains a need for a comprehensive framework that synthesises the current state of knowledge on remote sensing's role in biodiversity research. This review addresses this research gap by providing an integrated perspective on the applications, opportunities, and challenges of remote sensing technologies in biodiversity monitoring. Specifically, this review aims to bridge the gap between remote sensing and biodiversity science by highlighting the latest advances, identifying key research priorities, and discussing the potential for informing conservation decisions. By exploring the intersection of remote sensing and biodiversity science, this review provides new insights into the development of effective monitoring strategies, the improvement of biodiversity models, and the enhancement of conservation outcomes.

2. Materials and methods

This systematic review aims to provide a comprehensive overview of the role of remote sensing in biodiversity research. A thorough literature search was conducted using major scientific databases, including Web of Science, Scopus, Google Scholar, and PubMed. The search terms used included a combination of keywords related to remote sensing and biodiversity, such as "remote sensing," "biodiversity," "conservation," "ecosystem health," and "Earth Observations." Studies were included in the review if they were published in peer-reviewed journals, focused on the application of remote sensing in biodiversity research, were written in English, and published between 2000 and 2023. Studies that were not directly related to remote sensing and biodiversity, including conference proceedings, book chapters, and review articles, were excluded. The search results were screened based on title, abstract, and full-text review, and relevant studies were analysed with data extracted on study design, remote sensing technology used, biodiversity metrics, and key findings. The extracted data were synthesised narratively, with a focus on identifying patterns, themes, and gaps in the literature, to provide a comprehensive overview of the current state of knowledge on remote sensing in biodiversity research.

3. Results and discussion

This review aimed to synthesise the current state of knowledge on the role of remote sensing in biodiversity research, highlighting its applications, opportunities, and challenges. The findings of this review reveal that remote sensing has revolutionised the field of biodiversity monitoring, enabling consistent assessment, monitoring, modelling, and reporting of biodiversity patterns and trends.

3.1 Biodiversity Monitoring through Remote Sensing:

Biodiversity remains difficult to quantify and monitor, as anthropogenic influences drive rapid changes in species composition, population dynamics, and ecosystem processes, affecting biological diversity at genetic, species, and ecosystem levels (Dornelas et al., 2013; Hillebrand et al., 2018). The Convention on Biological Diversity (CBD), established in 1992, has been instrumental in highlighting the urgent need to address the alarming rate of biodiversity loss (UN, 1992). Biodiversity decline remains one of the most pressing global challenges of our time (Pereira et al., 2010). Effective utilisation of cutting-edge technologies is crucial for tackling the complexities of biodiversity loss (Bibri et al., 2024). Advances in remote sensing, monitoring systems, and data analytics hold significant promise for enhancing biodiversity conservation (Turner et al., 2003). The United Nations' Sustainable Development

Goal 15 (SDG 15) for 2030 prioritises the protection, restoration, and sustainable use of terrestrial ecosystems (Yang et al., 2020). This goal encompasses several critical objectives, including the sustainable management of forests, recognising their vital role in maintaining ecosystem balance and supporting biodiversity (Dudley et al., 2005). Combatting desertification and land degradation, which threaten the livelihoods of millions of people worldwide (Abdi et al., 2013). Halting and reversing land degradation, to ensure the long-term health and productivity of terrestrial ecosystems (Ekka et al., 2023). As the natural world faces unprecedented pressures, tracking biodiversity change has emerged as a vital component of sustainable ecosystem management, essential for safeguarding the ecosystem services that support human well-being (Millennium Ecosystem Assessment, 2005).

Historically, biodiversity research has been driven by taxonomists, who have painstakingly explored, documented, and classified the diversity of plant and animal species (Waterton et al., 2013). Originating from Earth observation, remote sensing is a technology that utilises airborne or satellite-based sensors to collect and analyse data about objects, surfaces, or events from a distance (Fu et al., 2020). This technology detects and quantifies the energy reflected and radiated by the Earth's surface, enabling scientists to study and understand various environmental phenomena (Schaepman et al., 2009). Earth Observations (EO) employ remote sensing technologies to collect comprehensive data on the Earth's physical, chemical, and biological systems (Navalgund et al., 2007). EO is the utilisation of advanced sensors to capture high spatial resolution images, enabling the measurement of distinct spectral signals related to vegetation (Houborg et al., 2015). The Spectral Variation Hypothesis leverages unique spectral signatures of vegetation species to monitor and analyze their characteristics (Rossi et al., 2022). This approach enables three key applications, including Phenological monitoring, which tracks growth stages, flowering, and senescence. Biochemical analysis assesses pigment composition, water content, and nutrient status (Anderegg et al., 2020). Structural characterisation identifies leaf morphology, canopy architecture, and biomass distribution (Kamoske et al., 2021). Remote sensing data play a vital role in conservation efforts due to their unparalleled capability to capture the Earth's surface from various vantage points, spatial resolutions, and spectral frequencies (Wang et al., 2020). Remote sensing technology plays a vital role in understanding the natural world by enabling the observation of ecosystems, communities, and large organisms (Pettorelli et al., 2014). This innovative tool not only provides valuable insights into ecological context but also tracks environmental drivers of biodiversity change (Dornelas et al., 2013). Remote sensing stands alone as the state-of-the-art technology capable of delivering global coverage and continuous measurements of biodiversity condition (Avtar et al., 2020). The field of Earth Observations has undergone significant advancements, transforming our ability to study and understand the Earth's surface (Guo et al., 2015). Earth

Observations has evolved through several key stages, including beginning with aerial photographic studies, which laid the foundation for remote sensing. The field has progressed to high-resolution imaging (Cracknell, 2018). The development of airborne 3D mapping enables the creation of three-dimensional representations of terrain and ecosystems (Jackson et al., 2020). Imaging spectroscopy has emerged as a cutting-edge technology, allowing scientists to analyse the chemical composition and physical properties of the Earth's surface (Ustin & Middleton, 2021). Recent breakthroughs in ecology, remote sensing, image processing, statistics, high-speed computation, and geographic information systems have revolutionised the study of biodiversity (Katikani et al., 2022). These advancements have created an unprecedented opportunity to expand the scope of biodiversity research, incorporating new dimensions and yielding a more nuanced understanding of biodiversity patterns (Kim & Byrne, 2006). The integration of in situ sensing methods has significantly enhanced remote sensing technologies, enabling a more comprehensive understanding of ecological systems (de Araujo Barbosa et al., 2015). With remote sensing and on-the-ground data collection using camera traps, UAVs, acoustic sensors, smartphones, and electronic transmission tags, researchers can gather high-resolution, localised data (Lahoz-Monfort & Magrath, 2021). This approach provides ground-truthing, real-time monitoring, and enhanced species detection, ultimately improving data accuracy and reliability (Hernandez-Santin et al., 2019). Remote sensing offers a significant advantage by augmenting and expanding upon traditional in situ observations, which are typically limited in scope, spatial coverage, and temporal resolution (Dorigo et al., 2007). The fusion of multispectral and radar remote sensing data presents a groundbreaking opportunity for enhanced biodiversity monitoring (Lausch et al., 2020). Recent advancements in hyperspectral technology have led to the development of several cutting-edge sensors, including AVIRIS-NG, Hyperspec, HySpex VNIR, and FirefIYE. Next-generation space-borne hyperspectral sensors, such as DESIS, PRISMA, EnMAP, and HySIS, have revolutionized Earth observation capabilities. These sensors provide high-resolution spectral data for various applications, including environmental monitoring, agricultural management, and natural resource conservation (Sishodia et al., 2020; Kumar et al., 2022). Unmanned Aerial Vehicles (UAVs) enable high-resolution ecological monitoring with spatial resolutions <5 cm and high temporal frequency (Manfreda et al., 2018). Unmanned Aerial Vehicles (UAVs) are increasingly being utilized as a highly effective tool for local-scale environmental monitoring (Adade et al., 2021). Their versatility and high-resolution imaging capabilities make them particularly well-suited for applications such as identifying land cover and benthic habitats, as well as conducting accurate wildlife censuses (Shortis & Abdo, 2016). The use of UAVs has been explored for semi-automatic reference data acquisition, focusing on estimating species cover for three invasive woody species: *Acacia dealbata*, *Pinus radiata*, and *Ulex europaeus*

(Kattenborn et al., 2019). The collected data was then upscaled to align with Sentinel-1 and Sentinel-2 satellite resolutions. UAV technology has demonstrated promise in monitoring invasive species, specifically *Acacia dealbata*, *Pinus radiata*, and *Ulex europaeus* (Phiri et al., 2020). By acquiring high-resolution reference data, researchers can accurately estimate species cover and scale up their findings to match the resolutions of Sentinel-1 and Sentinel-2 satellites (Zhang et al., 2019). UAV-based monitoring offers an innovative approach to tracking invasive species (Martin et al., 2018). A recent study targeted *Acacia dealbata*, *Pinus radiata*, and *Ulex europaeus*, utilising semi-automatic reference data acquisition and upscaling estimates to match the scales of Sentinel-1 and Sentinel-2 satellites (Kattenborn et al., 2019). Researchers employed a Convolutional Neural Network (CNN) model to automate the detection and counting of African elephants in South Africa's woodland savanna ecosystem (Galuszynski et al., 2022). WorldView-3 and 4 satellite data provided the high-resolution imagery necessary for accurate elephant identification (Duporge et al., 2021). The study in South Africa's savannas harnessed Convolutional Neural Network (CNN) technology to detect and count African elephants (Brickson et al., 2023). Leveraging WorldView-3 and 4 satellite data, the CNN model achieved remarkable accuracy in elephant identification and enumeration (Xu et al., 2024). Using WorldView-3 and 4 satellite imagery, scientists developed a Convolutional Neural Network (CNN) model to automatically detect and count African elephants in South Africa's woodland savannas (Brickson et al., 2023). This breakthrough application of deep learning technology enhances conservation efforts by providing precise estimates of elephant populations (Pimm et al., 2015).

3.2 Biodiversity Levels: The Foundation of Ecosystem Health:

Biodiversity is a multifaceted concept comprising three primary components are genetic, species, and ecosystem diversity (Singh, 2002). These interconnected components maintain the health and resilience of the natural world (Berkes & Ross, 2013). Genetic diversity refers to variations within a species' genetic makeup, species diversity represents the variety of species present, and ecosystem diversity encompasses differences among ecosystems (Vellend & Geber, 2005). Biodiversity operates at multiple hierarchical levels, from individual organisms to the global biosphere (Mace et al., 2021). This hierarchy

includes organisms, species populations, biological communities, ecosystems, landscapes, biomes, and the biosphere (Lidicker, 2008). Each level exhibits distinct structural and functional characteristics, with increasing complexity and emergent properties (Bickhard & Campbell, 2003). At the organismal level, structure and function are defined by individual characteristics (Folse & Roughgarden, 2010). Progressing to the population level reveals interactions among individuals of the same species (Barraquand et al., 2017). The community level introduces interactions among different species, while ecosystems show complex relationships between living and non-living components (Schmitz et al., 2015). Landscapes exhibit spatial heterogeneity, biomes display regional characteristics, and the biosphere encompasses the global web of ecosystems (DeFries et al., 1995). The community level plays a pivotal role in biodiversity monitoring, situated between species and ecosystem levels (Hooper et al., 2005). Species interactions and community composition influence ecosystem functioning, making this level essential for comprehensive assessments (Hooper et al., 2005).

Biodiversity can be understood through three attributes: composition, structure, and function. Organised into a nested hierarchy across four ecological levels, this framework provides a comprehensive understanding (Noos, 1990). At the regional landscape level, composition encompasses ecosystem variety, structure includes landscape patterns, and function involves ecological processes (Simensen et al., 2018). The community-ecosystem level focuses on species composition, habitat diversity, and functional interactions (Jain et al., 2014). The population-species level examines genetic composition, population structure, and functional traits (Funk et al., 2017). Finally, the genetic level considers genetic composition, genome organisation, and gene expression (Brawand et al., 2011). Recognising the interconnectedness of biodiversity's attributes across ecological scales enables holistic understanding and effective conservation strategies (Bennett et al., 2009).

Ecological assessment involves multiple spatial and temporal scales. Since no single organisational level is definitive, researchers employ varying resolutions tailored to specific questions (Ascough et al., 2008). This complexity has sparked a quest for suitable biodiversity indicators capable of capturing ecological nuances across genetic, species, ecosystem, and landscape levels (Crowder & Jabbour, 2014).

Table 1: Indicator variables for inventorying, monitoring, and assessing biodiversity at four levels of organisation (Noss, 1990; Reddy, 2021)

S.N.	Biodiversity levels/ attributes	Composition	Structure	Function	Inventory and monitoring tools
1	Community ecosystem	Biodiversity metrics include relative abundance, frequency, density, and diversity of species. These metrics are complemented by proportions of endemic, threatened, and invasive species, which highlight conservation priorities. Life form proportions reveal ecosystem structure, while the C4:C3 plant species ratio indicates adaptations to environmental conditions.	Vegetation characteristics (biomass and physiognomy), foliage density and layering, and horizontal canopy openness and gap proportions. Additionally, soil factors (texture, moisture, and nutrients) and topography (elevation, slope, and aspect) are examined.	Biomass and resource productivity, herbivory, and parasitism rates. Local extinction rates and patch dynamics, such as fine-scale disturbance processes, also provide valuable insights. Additionally, nutrient cycling rates and human intrusion rates and intensities are examined.	Remote sensing data and time series analysis to track changes. Physical habitat measures, field inventory censuses, and sampling provide ground-truth data. Multispecies habitat suitability models and mathematical indices, such as diversity and complexity metrics, offer additional insights.
2	Genetic composition	Allelic diversity, which measures the variety of gene variants. This includes the presence of rare alleles, deleterious recessives, and karyotypic variants, such as chromosomal abnormalities.	Census and effective population size indicate overall population viability. Genetic diversity is evaluated through heterozygosity, chromosomal or phenotypic polymorphism, and heritability. Generation overlap and genetic structure are also considered.	Key metrics such as inbreeding depression, outbreeding rate, and rate of genetic drift, which impact genetic diversity. Gene flow, mutation rate, and selection intensity also shape population genetics.	Electrophoresis, karyotypic analysis, and DNA sequencing, which examine genetic structure at the molecular level. Additionally, offspring-parent regression and sib analysis provide insights into heritability and genetic inheritance. Morphological analysis complements these methods, assessing physical traits.
3	Populations species	Absolute or relative abundance, frequency, and density, which describe population size and distribution. Importance Value Index (IVI) or Cover Value and biomass measurements provide additional insights into species'	Dispersion, or micro-distribution, which describes spatial arrangement at a local scale. Range, or macro-distribution, encompasses broader geographic distribution. Population structure, including factors like size, density, and age-	Demographic processes, such as birth and death rates, and life history traits, like growth and reproduction. Physiological characteristics, phenological patterns (e.g., migration,	Censuses, which provide direct population counts. Remote sensing technologies offer broader habitat insights. Habitat suitability models and species-habitat modelling identify potential areas for occupation.

		ecological significance and role within the ecosystem.	class distribution, is also examined. Additionally, habitat variables, such as vegetation type, climate, and topography, influence species distribution.	breeding), and population fluctuations also play crucial roles.	Population viability analysis (PVA) integrates these data to forecast population trends, extinction risk, and conservation effectiveness.
4	Regional landscape	Variation in species richness, or the number of species present. Endemism, or the presence of unique, locally restricted species, highlights areas of high conservation value. These patterns inform habitat classification, biodiversity assessments, and conservation prioritization.	Heterogeneity, or variation in habitat types, and patchiness, where distinct habitats are scattered throughout. Additional key features include porosity (gaps between patches), juxtaposition (adjacent habitats), and connectivity (linkages between patches). Fragmentation (breaking apart of habitats) and patch size also influence ecosystem dynamics. The perimeter-area ratio, which compares patch edge to interior habitat, affects species interactions and movement.	Disturbance processes, such as natural disasters or human activities, which alter landscape structure. Nutrient cycling rates influence resource availability. Patch persistence, or the stability of habitat patches, affects species resilience. Additionally, land use trends, such as deforestation or urbanization, drive changes in ecosystem composition and function.	Remote sensing data, which provides broad-scale environmental information. Geographic Information Systems (GIS) enable spatial analysis and mapping. Time series analysis reveals temporal patterns and trends. Spatial statistics help identify relationships between ecological variables. Landscape indices, such as fragmentation and patch size metrics, quantify ecosystem structure.

3.3 Essential biodiversity variables:

To enhance biodiversity monitoring, the Group on Earth Observations—Biodiversity Observation Network (GEO BON) introduced the innovative concept of Essential Biodiversity Variables (EBVs) (Kissling et al., 2015). These variables, observable from space, provide globally consistent metrics to track changes in biodiversity (O'Connor et al., 2020). Defined as "measurements required for studying, reporting, and managing biodiversity change," EBVs enable standardised monitoring and assessment of biodiversity trends, facilitating informed conservation decisions (Reddy et al., 2024). Biodiversity encompasses three core attributes: composition, structure, and function (Lyashevskaya & Farnsworth, 2012). This variable encompasses genetic composition, species populations, species traits, community composition, ecosystem structure, and ecosystem function, which can be tracked through various RS-EBVs, including genetic diversity indices, population size, phenology, species richness, Journal of Sustainability and Environmental Management (JOSEM)

habitat fragmentation, and net primary productivity (Lock et al., 2021).

Remote Sensing-Enabled Essential Biodiversity Variables (RS-EBVs) are categorised into four primary groups to monitor and assess biodiversity (Reddy, 2021). Firstly, Vegetation Community Composition is evaluated through taxonomic diversity and ecosystem composition by functional type (Laughlin et al., 2017). Secondly, Ecosystem Structure is assessed via land cover, ecosystem extent and distribution, fragmentation and heterogeneity, vegetation structure, canopy cover, and height (Coops et al., 2016). Thirdly, Ecosystem Function is monitored through land surface phenology, ocean greenness, disturbances, primary productivity, leaf area index, biomass, and nutrient retention (Zhang et al., 2013). Lastly, two critical categories analysed are species traits, including plant traits such as specific leaf area and leaf phenology, and Species Populations, encompassing species occurrence and distribution, as well as species abundance (Murray et al., 2002).

3.4 Biodiversity indicators:

Earth observation data play a vital role in monitoring the implementation of four strategic goals aimed at conserving biodiversity (Kuenzer et al., 2014). These goals are, firstly, addressing the underlying causes of biodiversity loss by integrating biodiversity considerations into government policies and societal practices (Rands et al., 2010). Secondly, reducing direct pressures on biodiversity involves promoting sustainable use and mitigating harmful impacts (Spangenberg, 2007). Thirdly, improving biodiversity status is ensured by safeguarding ecosystems, species, and genetic diversity (Corlett, 2020). Lastly, enhancing the benefits derived from biodiversity and ecosystem services ensures that all stakeholders reap the advantages of a healthy and thriving ecosystem (Pereira et al., 2005). The Aichi Biodiversity Targets, established to guide global conservation efforts, incorporate remote sensing capabilities in several areas (Petrou et al., 2015). Specifically, targets 4-15 have fully or partially remote-sensed components, enabling the utilisation of earth observation data to track progress (Secades et al., 2013; Ferreira et al., 2020). These targets include:

Target 4: Promoting sustainable production and consumption patterns.

Target 5: Halting habitat loss, fragmentation, and degradation.

Target 6: Ensuring sustainable exploitation of marine resources.

Target 7: Implementing sustainable management of natural resources.

Target 8: Reducing pollution's harmful impacts.

Target 9: Controlling invasive alien species.

Target 10: Protecting vulnerable ecosystems, such as coral reefs.

Target 11: Establishing and maintaining protected areas.

Target 12: Preventing extinctions of threatened species.

Target 14: Safeguarding ecosystem services.

Target 15: Enhancing ecosystem resilience.

Biodiversity indicators have been identified to track the health and resilience of ecosystems (Feld et al., 2010). These indicators include population and extinction risk trends of target species, as well as forest specialists in restored forests, and species providing essential ecosystem services (Noss, 1999). Additional indicators are trends in invasive alien species, and climatic impacts on populations, shifts in vulnerable ecosystem boundaries, and changes in ecosystem condition and vulnerability, impacts of climate change on community composition, extent and type of forests, mangroves, seagrass, and coral reefs, habitats providing carbon storage, such as wetlands and peatlands, delivery of multiple ecosystem services, including pollination, pest control, and nutrient cycling, condition and vulnerability of ecosystems, including fragmentation, degradation, and resilience (Sahavacharin et al., 2022). Monitoring these indicators enables assessment of

biodiversity trends, identification of conservation priorities, and evaluation of effective management strategies (Stem et al., 2005).

3.5 Biodiversity inventory:

Biodiversity inventories should follow a top-down methodology, systematically moving from broad to fine scales (Eicken et al., 2021). This involves a regional landscape assessment, providing an overview of ecosystem characteristics, community-ecosystem analysis, exploring species interactions and environmental relationships, population-species examination, investigating species-specific trends and dynamics, and genetic-level analysis, which reveals intra-species diversity (Syrbe & Walz, 2012). An accurate inventory of species distributions is vital for ecology and resource management (Stockwell & Peterson, 2002). This fundamental information supports conservation planning and habitat protection, sustainable resource management, ecosystem resilience and biodiversity conservation, climate change research and adaptation, informed decision-making at local, regional, and global scales (Reside et al., 2018).

Accurate biodiversity assessment requires spatially referenced field data and remote sensing-based stratification (Nagendra, 2001). This integrated approach enables the analysis of vegetation structure, composition, and diversity, the identification of indicators such as species richness and threatened species, the precise estimation of species distributions and habitat classifications, and improved conservation decision-making (Weiers et al., 2004). Statistically designed inventories optimise spatial precision, incorporating spatial and spectral properties (Wulder, 1998). This framework supports high-priority conservation efforts, focusing on endemic and threatened species, as well as ecologically unique habitats (Hierl et al., 2008).

3.6 Scale:

In numerous remote sensing applications, the scale of analysis is often determined arbitrarily or driven by technical constraints, rather than being guided by the ecological or environmental processes being studied (Huylenbroeck et al., 2020). When studying biodiversity and ecological phenomena, multiple scales are involved (Leibold et al., 2004). These scales can be categorized into four main types: 1) Spatial scale, which depends on two factors: grain (resolution) and extent (study area size). Grain encompasses spatial, spectral, radiometric, and temporal resolution (Teillet et al., 1997). 2) Biological scale, ranging from genes and species to ecosystems and biomes, highlighting the hierarchical structure of biodiversity (Duncan et al., 2015). 3) Temporal scale, focusing on variations across different timeframes, from daily and seasonal changes to annual and decadal fluctuations (Gastineau et al., 2013). 4) Spectral scale, which considers the sensor's ability to distinguish fine wavelength intervals, characterised by

spectral range and resolution (Aasen et al., 2018). It is crucial to recognise that biodiversity levels (genetic, species, ecosystem, and biome) possess a scale dimension, but these levels are distinct from scales themselves (Pavoine & Bonsall, 2011). While satellite-based remote sensing technology has advanced significantly, theoretically allowing for the distinction of top canopy level plant species based on spectral, radiometric, and spatial resolution, practical applications reveal limitations (Ali et al., 2016). In reality, reliable results are more consistently achieved at the community level of vegetation, rather than at the level of individual species identification (Gotelli & Colwell, 2001). This is because vegetation communities represent a more cohesive and scalable unit of analysis (Urban et al., 2002). The concept of a community is scale-dependent, meaning it is only meaningful within a specific range of observation scales (Wheatley & Johnson, 2009). At certain scales, patterns and relationships between species become apparent, enabling more accurate assessments and classifications (Fassnacht et al., 2016).

Remote sensing-based studies of vegetation attributes are significantly influenced by the scale of measurement, which varies greatly depending on the sensor used (Houborg et al., 2015). With over 100 optical and radar sensors currently in orbit, there's substantial diversity in spatial, spectral, radiometric, and temporal resolutions (Steele-Dunne et al., 2017). Spatial resolution, for instance, ranges from very high (0.5-5m) for sensors like Cartosat-2 and 3 series, IKONOS, and QuickBird, to high (10m) for sensors such as LISS-IV, Sentinel-2, and ALOS AVNIR-2, and medium to low resolutions (100m or coarser) for sensors like SPOT, ASTER, Landsat OLI, MODIS, and Suomi NPP VIIRS (Hedley et al., 2012).

The size of the ground resolution cell determines the scale of detectable features, and individual pixels often combine reflectance from multiple features (Bai et al., 2016). The importance of selecting the appropriate sensor for specific research applications (Ingelrest et al., 2010). Furthermore, the growing trend towards utilising Google Earth and Google Earth Engine for biodiversity assessment, inventory, and monitoring offers new opportunities for research and applications (Amani et al., 2020).

The Sentinel-2 satellite constellation stands out for its unparalleled capabilities in vegetation monitoring, boasting a high temporal revisit frequency of just 5 days and a 10-meter spatial resolution (Scarpa et al., 2018). This enables frequent assessments of plant status, detailed analysis of phenological phases, and accurate change detection (Piao et al., 2019). The extensive data availability of Sentinel-2, with numerous cloud-free scenes captured for each area of interest, sets new standards for vegetation analysis, facilitating improved crop management, enhanced land cover classification, and more accurate biodiversity assessments (Misra et al., 2020).

Remote sensing employs two main sensor types are passive and active. Passive sensors, such as multispectral and imaging spectrometers, measure ecosystem function and composition, vegetation phenology, and disturbance regimes (Dronova & Taddeo, 2022). Active sensors, including radar and LiDAR, measure ecosystem structure, such as tree height and canopy density, as well as woody structural and hydrological characteristics (Lefsky et al., 2002). Combining these sensors provides a holistic view of ecosystems (Serrano et al., 2018).

LiDAR technology has revolutionised ecosystem mapping by enabling direct estimation of spatially explicit three-dimensional canopy structures (Beland et al., 2019). NASA's Global Ecosystem Dynamics and Investigation (GEDI) mission has successfully integrated full-waveform laser data to study forest structure, shedding light on its relationships with tree species richness and habitat degradation (Duncanson et al., 2022).

Over the past seven years, there has been a significant surge in the number of earth observation satellites and sensors used to measure and model biodiversity from space (Bush et al., 2017). Passive sensors, which capture reflected and emitted energy, dominate biodiversity studies (Zwerts et al., 2021). Commercial satellites, such as QuickBird and IKONOS, offer high-resolution data, while NASA's Landsat series is widely used due to its ease of access, extensive time series, and affordability (Ouma, 2016). Radar sensors, particularly active spaceborne sensors, play a crucial role in biodiversity studies, as they can penetrate cloud cover and capture imagery day and night, regardless of weather conditions (Janga et al., 2023).

Table 2: Satellites with passive or active sensors that can be used to measure and model biodiversity from space (Gillespie et al., 2008)

Sl. No.	Satellite (Sensor)	Pixel size (m)	Bands	References
Passive sensors		Spectral bands		
1.	QuickBird 2	0.6, 2.5	5	Bergen et al., 2007
2.	IKONOS 2	1, 4	5	Bawa and Seidler, 1998
3.	OrbView 3	1, 4	5	Gillespie et al., 2008
4.	Landsat (TM, ETM+)	15, 30,	7-8	Foody, 2004

		60, 120		
5.	IRS (LISS III)	5, 23, 70	5	Bawa et al., 2002
6.	EOS (ASTER)	15, 30, 90	14	Asner et al., 2004
7.	SPOT	2.5, 10, 1150	5	Argos, 2008
8.	EOS (Hyperion)	30	220	Argos, 2008
9.	ALOS	2.5, 10	4	Gillespie et al., 2008
10.	NOAA (AVHRR)	1100	5	Boyd and Danson, 2005
11.	EOS (MODIS)	250, 500, 1000	36	Bergen et al., 2007
Active sensors		Bands		
12.	SRTM	30, 90	X, C	Bawa and Seidler, 1998
13.	QSCAT	2500	Ku	Argos, 2008
14.	Radarsat	9-100	C	Achard et al., 2002
15.	SIR-C	10-200	X, C, L	Achard et al., 2002
16.	TRMM (TMI)	18000	X, K, Ka, W	Achard et al., 2002
17.	ERS-2	26	C	Gillespie et al., 2008
18.	Envisat	30	C	Gillespie et al., 2008

3.7 Biodiversity models:

Modelling biodiversity patterns can be approached at various levels, including species, community, and ecosystem levels (Ferrier & Guisan, 2006). To model species richness and ecological niches, researchers utilise geo-referenced occurrence data in conjunction with digital maps that represent land cover, topography, and climatic variables (Chauvier et al., 2021). Species distribution modelling (SDM) is particularly useful for identifying knowledge gaps and informing sampling

design (Feldman et al., 2021). Furthermore, spatial models are available for analysing biodiversity distribution at the landscape level (Roy & Tomar, 2000). Biodiversity models are essential for understanding the future of biodiversity, which is constantly evolving due to numerous factors. Process-based models, combined with long-term measurements of change from Earth observations, can facilitate the development of early warning systems (Balsamo et al., 2018). Moreover, the predictive ability of radar-derived data has been validated through external studies focusing on species composition, such as those involving birds, mammals, crabs, and butterflies (Beland et al., 2019).

3.8 Habitat:

A habitat is a complex, three-dimensional entity encompassing air, water, and ground spaces, along with their interfaces (Tokeshi & Arakaki, 2012). It comprises both the physical environment and the diverse communities of plants and animals that inhabit it (Sousa, 1984). Habitats provide the necessary environmental conditions for the survival and reproduction of species (Kearney, 2006). Habitats can be characterized at various scales, ranging from microhabitats (m² scales) to meso-habitats and macro-habitats (100s m²–km² scales) (Davies et al., 2005). Understanding habitat dynamics is crucial for biodiversity conservation. Remote sensing enables indirect monitoring of biodiversity by leveraging environmental parameters as proxies (Turner et al., 2003). To indicators tracked through satellite, airborne, and near-surface remote sensing include habitat type, habitat structure, habitat quality, and stand condition (Lausch et al., 2016).

Habitat heterogeneity plays a crucial role in species diversity, with a well-established relationship between species richness and habitat diversity (Lundholm, 2009). Essentially, as habitat heterogeneity increases, species richness also increases, and this correlation holds true across various scales (Stein et al., 2014). This relationship enables researchers to map species diversity effectively (Hughes et al., 2021). Species often have specific habitat requirements, whether confined to discrete habitats or spanning multiple habitat types (Rosenfeld, 2003). By leveraging remotely sensed data, these habitats can be accurately identified and mapped (Corbane et al., 2015). Combining this information with data on habitat condition, extent, and species-specific requirements, researchers can generate precise estimates of potential species ranges and patterns of species richness, utilising maps of vegetation and land cover to inform their analyses (Yalcin & Leroux, 2017). Research has revealed a positive correlation between variations in the Normalised Difference Vegetation Index (NDVI) and measured species richness, as well as the weighted abundance of mapped vegetation types (Gould, 2000). This study employed ecological rule-based to classify vegetation types and assess natural forest cover change and fragmentation in South Asia over the past eight decades (Stibig et al., 2014). Furthermore, the use of

Moderate Resolution Imaging Spectroradiometer (MODIS)-based dynamic habitat indices successfully explained global variations in species richness among amphibians, birds, and mammals (Nagendra et al., 2013).

3.9 Vegetation health:

Variations in pigment content reveal valuable information about the physiological state of leaves. Chlorophyll levels, for instance, decline rapidly when plants face stress or undergo leaf senescence (Hörtensteiner, 2006). Vegetation health is a multifaceted concept, encompassing both vegetation structure and plant function, including greenness index, leaf pigment index, and light use efficiency (Liew et al., 2008). To assess vegetation health, researchers employ spectral vegetation indices, which combine surface reflectance data from two or more wavelengths (Xue & Su, 2017). These indices highlight specific vegetation conditions, such as Normalised Difference Vegetation Index (NDVI), Leaf Area Index (LAI), Ratio Vegetation Index (RVI), Soil-Adjusted Vegetation Index (SAVI), Difference Vegetation Index (DVI), Enhanced Vegetation Index (EVI), Atmospherically Resistant Vegetation Index (ARVI), Photochemical Reflectance Index (PRI), Structure Insensitive Pigment Index (SIPI), and Red Edge (Basso et al., 2004).

Time series analysis of temperature and precipitation data in Greece from 1950 to 2009 reveals a disturbing trend: climate change is having a detrimental impact on forest health, contributing to the decline of tree species (Peñuelas & Sardans, 2021). This dieback can be attributed, in part, to outbreaks of pathogens that thrive under specific climatic conditions (Goberville et al., 2016). Fortunately, advancements in hyperspectral technology have enabled researchers to monitor forest health more effectively (Ecke et al., 2022). By estimating foliar chemistry, scientists can gauge the overall well-being of forests. Foliar chemistry, in turn, is a key indicator of ecosystem functioning, as it reflects crucial biochemical processes such as photosynthesis, respiration, and litter decomposition (Ghaley et al., 2014). These processes are intimately tied to the concentration of essential nutrients, such as nitrogen, carbon, and leaf pigments, providing valuable insights into the intricate relationships within forest ecosystems (Fenn et al., 1998).

3.10 Ecosystem services:

The spatially explicit nature of remotely sensed data enables the identification of the extent and location of ecosystem services (Andrew et al., 2014). This technology offers a cost-effective solution for quantifying and mapping ecosystem services, with the added advantage of continuous monitoring capabilities

(Njue et al., 2019). Land cover serves as a reliable proxy measure of ecosystem services due to its connections to various critical factors, including carbon storage, plant diversity, resource types, water availability, climate regulation, weather regulation, and watershed protection (Koschke et al., 2012). To analyze vegetation status, multivariate vegetation indices are essential for capturing gradual changes in land cover (Peijun et al., 2010). Research has established a positive correlation between species richness and spectral diversity (Rossi et al., 2022). A framework for assessing ecosystem services using remote sensing involves linking spectral data to ecosystem services and utilising canopy and surface soil status as surrogate information (Andrew et al., 2014). This integrated approach combines Earth Observations with socioeconomic data and model-based analysis to support comprehensive assessments of ecosystem service supply, demand, benefits, and limitations (Cord et al., 2017).

3.11 Biogeochemical heterogeneity:

The Earth's biological systems rely on the cyclical exchange of essential elements, but human activities are significantly disrupting these delicate balances (Meybeck, 2003). Notably, atmospheric carbon dioxide levels have surged by approximately 40% since pre-industrial times (Hofmann et al., 2009). Similarly, nitrogen, phosphorus, and other vital elements have also seen substantial increases (Vitousek et al., 2010). These altered biogeochemical cycles, combined with the pressures of climate change and climatic variability, significantly increase the vulnerability of biodiversity, placing ecosystems and species at heightened risk (Cusack et al., 2016). The interplay between biotic and abiotic diversity has a profound impact on biogeochemical heterogeneity across various scales (Townsend et al., 2008). At the local level, the diversity of plant species, or floristic diversity, introduces variations in chemical and structural traits that influence ecosystem processes such as productivity, decomposition, and nutrient cycling (Mazzoleni et al., 2007). Moving to the regional scale, factors such as soil age, soil chemistry, landscape dynamics, and disturbances create variations in limiting nutrients, further contributing to biogeochemical heterogeneity (Smith et al., 2015). Notably, remote sensing technologies play a crucial role in monitoring carbon, water, and soil dynamics, which are closely tied to ecosystem services (Smith et al., 2019). In fact, vegetation plays a critical role in the carbon exchange between the terrestrial biosphere and the atmosphere, mediating up to 90% of this exchange. The importance of understanding the complex relationships between biodiversity, ecosystem processes, and biogeochemical cycles in maintaining healthy and functioning ecosystems (Berhe et al., 2018). Airborne hyperspectral

imaging and laser-scanning systems have revolutionised the study of tropical forests by providing detailed measurements of their structure, light environment, and canopy chemistry at the local scale (De Almeida et al., 2021). These measurements across various axes of variation, including climate, landform, soil type, and community shifts, researchers can gain new spatial insights into ecosystem function (Wang et al., 2022). This is particularly important for addressing a significant knowledge gap: the effects of biogeochemical heterogeneity on tropical ecosystem function have historically been poorly captured in estimates (Bustamante et al., 2016). This shortfall, dynamic global vegetation models (DGVMs) simulate the functioning and distribution of plant functional types, shedding light on climate-vegetation interactions and the distribution of vegetation types (Trugman et al., 2019). Moreover, DGVMs integrate with carbon and nitrogen cycles to simulate biogeochemistry and growth, providing a comprehensive understanding of tropical forest ecosystems (Sitch et al., 2008). With these advanced technologies and modelling tools, scientists can develop more accurate and nuanced predictions of ecosystem function and better mitigate the impacts of environmental change (Villa et al., 2014).

3.12 Biodiversity Informatics:

Biodiversity Informatics is a multidisciplinary field that leverages information technologies to manage, analyse, and interpret species-level data (Parr et al., 2012). This field utilises computational methods and algorithms to explore and understand the complex relationships between species and their environments (Olden et al., 2008). Integrating ecologically relevant data from genes to ecosystems is crucial for advancing our understanding of biodiversity and informing effective natural resource management strategies (Cavender-Bares et al., 2022). This integration is facilitated by biodiversity informatics, a multidisciplinary field that connects various dimensions of organismal biology, phylogenetics, taxonomy, ecology, biogeography, geo-informatics, and conservation (Dos Santos, 2003). A prime example of this is the National Biodiversity Data Centre of Ireland, which provides a cutting-edge infrastructure for the entire information cycle, encompassing data management, coordination, publication, and reporting on biodiversity data (Stefanni et al., 2022). To further conservation efforts, there is a pressing need for the development of cross-disciplinary biodiversity informatics infrastructure and standardised data (Heberling et al., 2021). By applying informatics techniques to biodiversity information, researchers can uncover new insights, analyse existing data in innovative ways, and predict future scenarios (Canhos et al., 2004). This fusion of technology and biodiversity research has the potential to revolutionise our understanding of the natural world and inform evidence-based conservation strategies (Bhambri & Kautish, 2024).

3.13 Conservation planning:

Human activities, particularly changes in land cover, pose significant threats to biodiversity (Hu et al., 2021). Remote sensing offers a valuable tool for monitoring habitat loss, fragmentation, and degradation (Dupuis et al., 2020). By analysing satellite images, researchers can derive information on landscape patterns and shape indices, crucial for conservation efforts. Tailoring the process to specific land-cover types can optimise resources, especially in resource-limited applications. Remote sensing can focus on specific classes of interest, streamlining efforts and reducing problems associated with standard classification analysis (Ball et al., 2017). Conserving biodiversity requires accurate, up-to-date information (Stephenson & Stengel, 2020). Remote sensing provides a repeatable, systematic, and spatially exhaustive source of data on variables impacting biodiversity, such as productivity, disturbance, and land cover (Strittholt et al., 2007). This is particularly valuable in remote, inaccessible regions. After establishing reserves, remote sensing continues to play a crucial role in monitoring effectiveness and comparing changes inside and outside protected areas (Wiens et al., 2009). The importance of areas outside reserves, such as logged forests and secondary forests, is that they can significantly contribute to biodiversity conservation (Chazdon et al., 2009). Remote sensing supports landscape-scale biodiversity conservation by providing a synoptic overview of the entire landscape (Kacic & Kuenzer, 2022). Its data can inform general biodiversity assessments, including the Biodiversity Intactness Index, aiding in monitoring and decision-making (Underwood et al., 2018). Overall, remote sensing is a vital tool for biodiversity conservation, offering efficient, cost-effective, and spatially comprehensive information for prioritising conservation efforts, monitoring protected areas, and informing biodiversity assessments (Hoffmann, 2022).

3.14 Important Aspects of Remote Sensing in Biodiversity Conservation

1. **Monitoring Habitat Loss and Fragmentation:** Remote sensing enables the tracking of changes in land cover and habitat fragmentation, crucial for understanding biodiversity decline (Dupuis et al., 2020).
2. **Conservation Prioritisation:** By providing spatially comprehensive data, remote sensing helps prioritise areas for conservation efforts, ensuring efficient use of resources (Hoffmann, 2022).
3. **Protected Area Monitoring:** Remote sensing facilitates the monitoring of protected areas, allowing for the assessment of conservation effectiveness and comparison with surrounding areas (Wiens et al., 2009).
4. **Landscape-Scale Conservation:** Remote sensing supports landscape-scale biodiversity conservation by offering a broad overview of the landscape, enabling informed decision-making (Kacic & Kuenzer, 2022).

4. Conclusion

Biodiversity monitoring is a multifaceted field that requires the integration of various components to effectively map, monitor, and model biodiversity. While in situ data are essential, they are insufficient on their own for tracking biodiversity patterns and achieving conservation objectives. Fortunately, advancements in remote sensing techniques hold great promise for accurately measuring biodiversity at both community and species levels. Remote sensing has immense potential, but field-based species exploration remains crucial, as it plays a unique role in comprehensively covering biodiversity. The integration of remote sensing and field-based data will facilitate the systematic use of information for conservation efforts, ultimately enhancing our ability to protect and preserve biodiversity.

Over the last seven years, space-borne imagery has made significant contributions to the science of biogeography and biodiversity. Future research should focus on incorporating recent and new space-borne sensors, integrating available data from passive and active imagery, and collecting and disseminating high-quality field data. Recent developments in satellite and sensor technology will further improve our abilities to study biogeographical patterns of biodiversity from space. High-resolution spectral satellites will enable data acquisition at enhanced spatial, spectral, and radiometric resolutions, allowing for the mapping of individual species. Radar satellites, such as SAR-Lupe, COSMO-SkyMed, and TerraSAR-X, will provide valuable multidimensional data sets, including vegetation structure, biomass, and land cover.

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