

Article

Verifiable Nature Units (VNUs): A Scalable Outcome-Based Framework for Valorising Natural Capital

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Abstract

Global biodiversity loss undermines ecological integrity and natural capital, yet many biodiversity–finance mechanisms still reward activities rather than verified ecological outcomes, reducing accountability and investor confidence. We introduce Verifiable Nature Units (VNUs), a standardised, outcome-based framework that approximates annual change in ecological integrity at 1 km² resolution. The framework combines an anthropogenic disturbance-based Habitat Intactness (HI) index, derived from remote sensing and spatial datasets, with an Indicator Species (IS) layer estimated through repeated on-site monitoring of selected indicator species across at least three functional guilds. Baselines, tolerance buffers, eligibility criteria, and independent verification requirements translate measured outcomes into investable units. In Majete Wildlife Reserve (711 km²), southern Malawi, HI remained consistently high (0.99) from 2018–2024, with localised declines linked to park infrastructure and extreme weather events. Occupancy analyses for six indicator species across four functional guilds showed high and stable park-level performance from 2021–2025, resulting in all 711 potential VNUs being eligible for issuance in 2024/5. The VNU is not an exhaustive measure of ecological integrity; it is a practical, auditable MRV approach for outcome-based biodiversity finance that can adapt as monitoring systems and ecological metrics mature.

Keywords: biodiversity credits; biodiversity finance; ecological integrity; habitat intactness; indicator species; monitoring and reporting; occupancy modelling; verifiable nature units



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1. Introduction

Biodiversity loss and ecological degradation are eroding the natural capital (i.e., the stock of natural assets and ecosystem services that generate benefits for people and economies) that underpins human well-being, climate stability, and economic development. The IPBES ‘Global Assessment’ documents a widespread decline in species and ecosystem condition, with profound consequences for food security, healthcare, and cultural values [1]. More recent syntheses underscore the persistence of these trends, coupled with increasingly complex biodiversity, climate, and development pathways [2,3]. Further macroeconomic analyses indicate that ~55% of global GDP is moderate-to-highly dependent on nature,

placing biodiversity loss among the most severe systemic risks to our economies and societies [4]. Despite this dependency, the economic value of nature is arguably underestimated, as this capital is rarely priced or measured consistently, and remains peripheral to mainstream investment decisions, which generally favour short-term, extractive returns over long-term ecological integrity [5–7]. This global misalignment between where value is generated (i.e., healthy ecosystems) and where returns are realised (e.g., often nature-negative activities) is reflected in the biodiversity finance gap: an estimated USD 700–950 billion per year is required to meet global biodiversity targets, compared with current spending of USD ~150 billion (16–21%), leaving an annual shortfall of around USD 600–800 billion [8,9]. In contrast, public subsidies that drive habitat loss and other nature-negative outcomes are estimated at USD ≥ 1 trillion per annum, with agriculture and fossil fuels among the largest contributors, while restoration alone requires only several hundred billion annually [9]. Land use change drives much of this imbalance, with current assessments attributing ~90% of global deforestation between 2000 and 2018 to agricultural expansion, of which cropland expansion is responsible for ~50% and livestock grazing for ~39% [10–12]. More recent assessments further identify commodity-linked agriculture as a dominant driver of tropical deforestation [13]. Agricultural landscapes and associated infrastructure often generate higher immediate private returns than conservation or restoration, even where long-term social and ecological costs are substantial [14]. Unless nature stewardship can compete as a financially viable land use option, landscapes with high ecological integrity will continue to be converted to more lucrative but ecologically degrading uses [15]. This conversion pressure is ultimately an incentives-and-measurement problem, where nature stewardship cannot compete as a land use unless ecological outcomes can be quantified credibly, compared consistently, and rewarded accordingly.

Aligning financial incentives with biodiversity conservation and restoration requires a globally accepted approach to quantifying changes in biodiversity performance [16]; however, this remains challenging to observe directly and quantify comparatively over large spatio-temporal scales. Ecological integrity (EI) provides a potentially unifying method of describing protected area condition in a meaningful way for both biodiversity conservation and communities, whose subsistence and alternative livelihood options depend on the services generated by functional ecosystems [2,3]. EI is commonly framed as the extent to which ecosystem structure, composition and function resemble an explicit range of reference conditions, recognising that in many landscapes ‘minimally disturbed’ baselines are uncertain or absent and reference conditions may instead be defined using locally appropriate ecosystem functionality benchmarks [17]. This framing is a central tenet of the ‘nature-positive’ development and the Kunming–Montreal Global Biodiversity Framework [18,19]. A range of global indices, such as the Biodiversity Intactness Index (BII), Forest Landscape Integrity Index (FLII), and Ecosystem Integrity Index (EII), combine land use, human pressures, and biodiversity information to generate such scalable measures of ecosystem condition, which are increasingly used to identify and prioritise high-integrity areas for protection and restoration, as well as assess cumulative impacts and track progress towards global targets [20–22]. It has also been argued that the BII may underestimate losses where declines are concentrated among functionally distinctive species [23]. However, integrity should ultimately be realised and managed within social–ecological systems, where institutions, livelihoods, culture and historical context shape both local pressures and responses [24]. Yet, a critical limitation persists in that these globally pooled or proxy-based indices may lack accuracy and interpretability at finer spatial granularities. This scale mismatch limits their applicability for the project scale where most management decisions and financial transactions occur, particularly in data-poor yet biodiverse regions [25]. Complementary local assessments may use suites of metrics

(e.g., species richness, community composition, functional guilds, and habitat structure) benchmarked against reference range conditions. While these offer ecologically nuanced insights, they are often data- and expertise-intensive, which limits their replicability across multiple landscapes and constrains their scalability where undisturbed reference state ranges are uncertain or absent [26,27]. A pragmatic solution to address these challenges would be to use indicators that provide simplified representations of underlying ecological conditions [26,28], such as Habitat Intactness (HI) and Indicator Species (IS), where trends in unsustainable disturbances and carefully selected taxa could act as integrative signals of ecological condition. This approach would align with natural-capital and ecosystem service approaches, which seek to make biodiversity value more visible through biophysical and monetary valuation, spatial planning, and nature-based solutions [7]. While ecosystem service valuation can inform land use planning, compensation schemes and investments [29], operationalising approaches that align financial incentives with ecological performance remains fragmented and rarely tied to standardised, outcome-based units that link integrity to investable assets. Accordingly, a critical gap remains in that there is still no widely adopted, fine-resolution metric that can function across diverse and data-limited settings as a verifiable unit of account for biodiversity-aligned finance, despite the clear potential of integrity measures and indicator guilds to translate ecological outcomes into decision-relevant units for management, policy, and finance [6].

Recent reviews of biodiversity finance highlight several barriers that prevent capital from flowing towards nature-positive outcomes at scale: (i) a lack of trust in metrics, (ii) fragmentation of indicators, (iii) high transaction costs for bespoke monitoring, and (iv) an ongoing dominance of carbon-centric frameworks that risk sidelining biodiversity and EI [30–32]. Importantly, carbon-focused incentives do not automatically deliver biodiversity co-benefits, and biodiversity outcomes can vary widely among carbon-focused interventions [33]. Such industry fragmentation is further compounded by a proliferation of standards and measurement approaches, which undermine interpretability, comparability, and ultimately confidence for investors and practitioners alike. Financial actors increasingly recognise nature-related risks and opportunities but often lack robust and comparable measures of ecological performance at the project level that can be embedded in contracts, financial products, and regulatory disclosure [34]. To address these barriers, there is a clear need for a standardised, outcome-based unit of nature that can integrate diverse indicators into a coherent and verifiable measure of ecological integrity that is credible, operationally scalable and explicitly designed to interface with financial instruments [35]. Climate finance provides an instructive analogue, where in the context of REDD+ and related forest carbon programmes, satellite-based assessments, well-defined baselines, and robust monitoring, reporting, and verification (MRV) protocols underpin results-based payments and carbon-linked financial products [36]. While biodiversity and ecological integrity are inherently multidimensional and cannot be treated as a direct ecological equivalent of one tonne of carbon, a comparable biodiversity-focused framework can still borrow the useful MRV architecture: clear baselines, monitored change, transparent uncertainty and independent verification. Such a framework should integrate structural measures of habitat condition (e.g., anthropogenic disturbance-based integrity indices derived from remote sensing and mapped human pressures) with response indicators such as trends in occupancy or abundance of ecologically functional species groups. It would also require explicit baselines, tolerance thresholds, and verification procedures so that measured change in integrity can be attributed to interventions and converted into units that trigger payments or contractual conditions over time.

To address these biodiversity finance barriers and strengthen the link between ecological outcomes and financial incentives, there is a clear need for a standardised, scalable

and auditable ecological accounting unit that is consistent across spatial scales, reduces fragmentation of metrics, lowers monitoring and verification costs, and is robust enough to build trust while enabling integration into finance-compatible, outcome-based instruments. To achieve this, we propose the Verifiable Nature Unit (VNU): a standardised outcomes framework that quantifies changes in EI at a defined spatial resolution and connects these outcomes to emerging nature finance mechanisms. The VNU is not intended to quantify biodiversity in full. Instead, it provides a globally relevant but locally adaptable accounting unit that approximates EI at a practical resolution. Each VNU represents a spatio-temporal cell (i.e., 1 km² per year), the state of which is defined by two components: (i) an inverted human footprint-style index used as a disturbance-based HI measure derived from remote sensing and human pressure layers; and (ii) an IS component derived from multi-year occupancy or equivalent repeat monitoring for locally relevant functional guilds. By combining these components into a composite EI score, with specified eligibility and verification rules, the VNU is designed to function as a relatively simple, yet robust, outcome-based unit that can underpin biodiversity credits, nature-linked loans, and other natural capital-based finance mechanisms. As such, it approximates EI for auditable accounting purposes and does not replace more comprehensive ecological assessments or studies.

This blend of top-down (HI) and bottom-up (IS) measures also ensures that monitoring remains accessible and repeatable for all nature stewards, which is particularly acute in the tropical biodiversity-rich but historically under-funded and understudied landscapes [25], where conservation outcomes are tightly coupled to local livelihoods, governance, and financial flows. African savanna and woodland ecosystems, for example, exemplify this interaction, as they support diverse assemblages of large mammals that structure ecosystems, which underpin tourism and cultural values, yet these systems have been disproportionately impacted by illegal hunting, land use change, and chronic under-investment [37]. In these systems, transitions from degraded and defaunated states to partial recovery have been achieved through changes in governance, long-term funding, and community partnerships [38]. Conservation models that align ecological outcomes with stable and diversified financing are thus urgently required. In this context, the African Parks Network (APN) provides a relevant testbed: APN manages a growing portfolio of protected areas under long-term delegated management agreements with African governments, combining delegated management authority, performance-based funding, intensive ecological monitoring and strong community partnerships as drivers of its landscape-scale conservation model. We therefore use a case study from Majete Wildlife Reserve (MWR) in southern Malawi, to demonstrate how VNUs can be operationalised as an integrated EI and natural capital accounting unit. MWR is particularly instructive, as prior to the government appointing a management partner through a management agreement associated with a long-term mandate and sustained funding in 2003, the reserve had lost most of its large mammal populations to over-exploitation [39,40]. Since then, reintroductions of elephant, rhinoceros, and lion, coupled with anti-poaching, park management, and community enterprise, have driven substantial ecological recovery and renewed tourism-based revenue. MWR therefore offers an informative test case, because it has undergone documented recovery and restoration interventions, with measurable changes in HI and IS trajectories that are directly relevant to sustained biodiversity finance mechanisms.

The overarching aim of this study is to propose the VNU methodology as a scalable, outcome-based framework for approximating EI and linking verified outcomes to financial instruments. The paper is organised around two practical research questions: (i) can structural habitat condition information and indicator guild responses be combined into a repeatable, auditable unit of ecological accounting; and (ii) can that unit be implemented at project scale using data streams that protected and conserved areas can realistically

maintain? Accordingly, the study has two objectives. Firstly, to define a conceptual framework in which each VNU corresponds to a 1 km² cell assessed annually, and EI is characterised using both a structural disturbance/pressure component (an HI index) and an ecological response component based on ecoregion-appropriate IS representing functional groups. Secondly, to demonstrate the practical implementation of this framework in MWR as a case study to quantify EI and issuance eligibility at per-cell resolution.

The methodological contribution of this study is not in the individual components of HI, indicator species or occupancy models, which are well established; rather, it lies in advancing the nature finance sector through the integration of these components into an auditable unit framework that can be used to underpin outcome-based grants, biodiversity credits and natural-capital investments, thereby enabling the mobilisation of additional funding for nature stewardship and contributing to the achievement of global biodiversity targets. To operationalise these objectives, we describe (i) the selection, mapping, scoring, and aggregation of multiple anthropogenic pressure layers into a continuous HI surface with explicit baselines and thresholds; (ii) an IS module based on multi-year occupancy modelling and segmented regression that yields classifications of stability, improvement or decline, and associated issuance scores; (iii) eligibility and verification rules that combine HI and IS into an overall EI score within an outcome-based MRV architecture; and (iv) application of IS and HI in MWR as a case study. By demonstrating both methodological rigour and practical scalability, we aim to provide a tangible pathway for integrating ecological outcomes into financial instruments, thereby strengthening incentives for nature stewardship to support global biodiversity goals.

2. Materials and Methods

2.1. Conceptual Framework and Scope

VNUs are defined as standardised, outcome-based units that measure the change in EI for discrete spatial cells (i.e., the project area) between repeated monitoring periods. The framework is broadly applicable across terrestrial and freshwater ecosystems. Its applicability to marine environments has not yet been established or tested and is therefore excluded from the current scope.

To simplify complex ecosystem interactions into measurable variables [28], the VNU framework integrates two complementary components: (i) HI—an inverted human footprint index as a scalable proxy for unsustainable disturbances, derived from Earth observation layers and mapped human pressures (Section 2.2); and (ii) IS—derived from response trends in ecologically meaningful and ecoregion-appropriate taxa (Table S1; Section 2.3). To improve interpretability and robustness across heterogeneous communities, these IS are grouped into functional guilds (i.e., sets of species that reflect comparable ecological roles and sensitivities), and scores are computed using the available indicator set rather than relying on any single species. This design is intended to reduce sensitivity to both natural biogeographic variation and incomplete species lists, such that the absence or non-detection of a particular species does not automatically reduce a cell score; instead, inference is based on detection-corrected trend models aggregated across IS.

For clarity, the framework has two linked quantitative components and one rule-based interpretive component. The quantitative components are the HI module, which processes remote sensing and mapped pressure data into annual cell-level disturbance and intactness scores, and the IS module, which estimates detection-corrected species and guild trends from repeated monitoring data and recorded effort. The rule-based component comprises the a priori indicator selection, pressure-weighting rationale, tolerance buffers, eligibility criteria and verification requirements that translate measured change into issuance decisions. These assumptions are not treated as qualitative results; they are

documented decision rules that can be audited, stress-tested and revised as additional evidence becomes available.

All analyses are reported on a common equal-area grid and annual timestep, where each cell represents a potential VNU. As input datasets are available at heterogeneous native resolutions (e.g., both spatially and temporally), we harmonise all variables to the VNU accounting unit (i.e., 1 km² per year) using variable-appropriate aggregation and temporal alignment procedures. A discrete global grid system (e.g., DGGRID [41]) is used to ensure consistent cell geometry and avoid latitudinal distortions inherent in geographic (i.e., degree-based) projections, before intersecting the grid with the area boundary to define the population of VNUs within a particular project. The same grid provides the spatio-temporal accounting framework for the HI and IS modules, as remote sensing and ancillary spatial layers underpin HI, while monitoring data (e.g., patrol segments, camera trap stations, acoustic recorders) are linked to grid cells to map effort and enable auditable project level aggregation for functional IS scoring. Cell-level outputs are retained to support spatial attribution, eligibility screening, and mapping of integrity outcomes.

EI is quantified by combining HI and IS scores, each on a 0–1 scale, within a common spatio-temporal grid to provide an integrative signal of change in ecological condition. This approach aligns with broader integrity frameworks, which describe integrity as a function of composition, structure and process [21,22,26,27,42]. However, the inclusion of locally derived IS data enables the approach to capture context-specific ecological dynamics [28], thereby improving its applicability and sensitivity at the project level.

The number of VNUs eligible for generation within a project area is determined by assessing whether EI is maintained or improved between monitoring periods (Section 2.4). Prior to issuance, VNUs must undergo independent verification to ensure the credibility and assurance required for their use within nature finance instruments. The verifier must confirm that the project complies with all methodological requirements and that the claimed ecological outcomes are authentic and accurately measured (Section 2.5 describes these requirements in further detail). Upon successful verification, VNUs are generated and recorded on a database or registry, depending on the applicable requirement of the nature financing instrument.

By leveraging globally available satellite data and locally feasible species data, this dual approach enables a transparent and replicable basis for MRV within outcome-linked conservation finance mechanisms [30,43] (Figure 1).

We applied the VNU framework to MWR (711 km²) in southern Malawi as a practical demonstration of implementation within a real protected-area monitoring system. We overlaid the reserve boundary with the equal-area 1 km² VNU grid (i.e., 711 intersecting cells) and used this common spatial accounting unit to link remote sensing human disturbance inputs and georeferenced monitoring data [11]. HI was calculated annually relative to a fixed baseline (i.e., providing at least a five-year trend) using globally available disturbance and locally curated protected-area layers (e.g., infrastructure and internal access networks), with APN operational records (e.g., patrol observations and registry/incident datasets) used to support disturbance attribution and interpretation where relevant, while maintaining a traceable input record suitable for an independent audit. Data processing and calculations were performed using Google Earth Engine [44] and ArcGIS Pro v3.6 [45]. IS performance was derived from standardised field monitoring (e.g., patrol observation records with effort and individual registries for indicator species), analysed with dynamic detection-corrected occupancy modelling in R v4.3.0 [46] with results underpinned by long-term absolute abundance records) and aggregated to functional indicator groups, with eligibility based on maintaining non-declining group performance under the predefined tolerance rules (i.e., $\epsilon_{ST} = 0.05$ and $\epsilon_{LT} = 0.10$). We then implemented issuance accounting by applying

the published eligibility criteria to the MWR grid to identify eligible cells and summarise issuance totals for the assessment period, retaining cell-level outputs and effort mapping to support spatial attribution, reproducibility and verification.

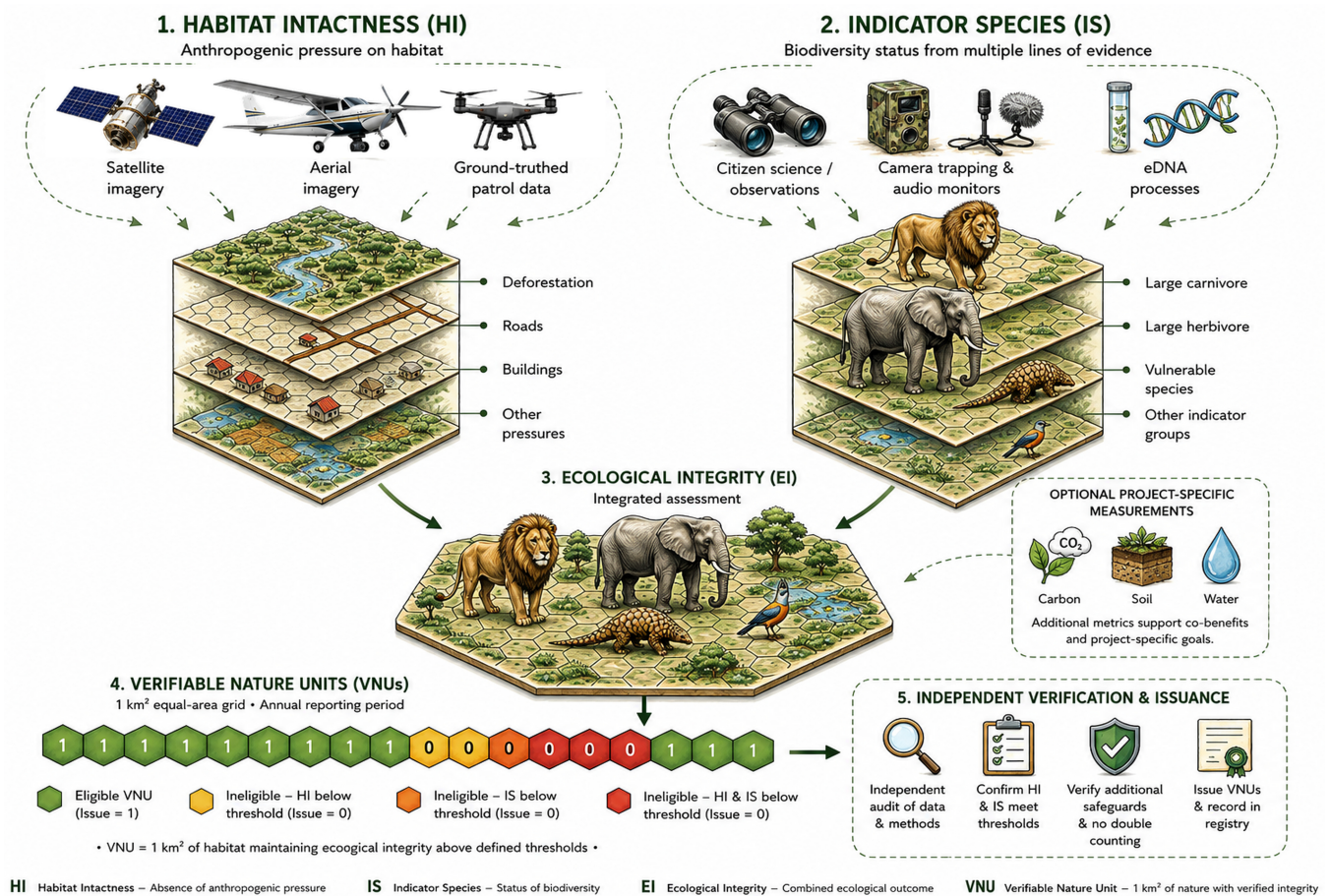


Figure 1. Conceptual workflow for generating Verifiable Nature Units (VNUs). Spatially explicit disturbance layers derived from Earth observation and mapped human pressures (e.g., deforestation, roads, buildings, cropland and other project-relevant pressures) are harmonised and combined to estimate habitat intactness for each 1 km² spatial unit (left). In parallel, standardised field monitoring (e.g., camera traps and related survey data) is used to estimate trends in indicator species grouped by functional roles (e.g., large carnivores, large herbivores, vulnerable taxa, specialists and other indicator groups; right). Additional measurements can be incorporated where required by project or buyer needs (e.g., carbon, soils, water). These components are integrated within a common grid to produce a composite ecological integrity assessment, which forms the basis for VNU eligibility and reporting.

2.2. Habitat Intactness (HI)

EI is closely linked to the extent to which ecosystems retain native structure, composition and function under contemporary human pressures and land use change [19]. Across many landscapes, including long-inhabited and co-managed systems, human presence and use are not inherently incompatible with biodiversity outcomes [18,44]. The practical question for outcome-based conservation finance is whether persistent, spatially explicit, or unsustainable pressures are likely to reduce habitat condition and thereby undermine ecological outcomes at the accounting scale of the VNU. We therefore quantify HI as the inverse of a composite, disturbance index derived from mapped anthropogenic pressures that are expected to cause sustained habitat modification or fragmentation (e.g., built infrastructure, deforestation and tree cover loss, cropland expansion, major and minor roads and railways, extractive activities, hydrological modification, and other durable

human footprints). Where relevant, additional locally derived layers (e.g., protected-area infrastructure, restoration footprints, waterpoint networks) and ground truth observations are incorporated to improve ecological realism and auditability.

HI draws on global products such as the Human Footprint and related human-pressure-mapping approaches [11,45–48], Global Forest Watch tree cover loss [49], cropland extent and change [12], and, where relevant, forest carbon flux proxies [50], supplemented by locally derived pressure layers, where available. These input layers occur at heterogeneous native spatial and temporal resolutions; therefore, to ensure consistency, a base raster layer is developed at the finest feasible spatial resolution (i.e., typically the finest common resolution among inputs; e.g., 10 m or 30 m). All input layers are aligned to this base raster and subsequently resampled and harmonised through variable-appropriate temporal alignment (e.g., annual summaries from higher-frequency products) and data-type-specific spatial processing (e.g., rasterisation of vector features).

Each pressure layer k is transformed to a common score $r_{\{k,p,t\}} \in [0, 1]$, where 0 represents no mapped disturbance and 1 represents complete disturbance for pixel p in year t . Polygon and binary layers (e.g., built environment, mine footprints, cropland and mapped clearance) are rasterised to the base grid and scored according to the proportion of the pixel affected. Linear features (e.g., roads, railways and internal access routes) are rasterised using pre-specified feature-class buffers so that the direct footprint and immediate edge-effect zone are captured consistently. Continuous layers (e.g., tree cover loss intensity, fire frequency or river disturbance where used) are scaled or thresholded into proportional disturbance values using rules defined before analysis and reported with the input record. Annual layers are aligned to year t , whereas persistent features remain active until removed or reclassified. Layers are then assigned relative weights W_k (Table S2) to reflect differences in expected ecological impact, persistence and reversibility, and these are normalised internally as $w_k = W_k / \max(W_k)$ before aggregation. Higher weights are assigned to disturbances that result in irreversible habitat transformation (e.g., built environments, mining), while lower weights are assigned to pressures that are partially reversible, more diffuse, or context-dependent in their ecological effects. Lower-weighted layers may still significantly affect ecological integrity, but their impacts are generally less permanent, more variable in severity, or occur at smaller spatial scales. With the aim of making assumptions explicit and auditable, these weights are specified a priori, informed by published human footprint approaches and expert-informed assumptions [11,20,21,45–48].

To avoid double-counting where pressure layers overlap spatially (e.g., tree cover loss co-occurring with built-up infrastructure), we combine pressures conservatively at the base pixel level using a dominant-pressure rule [11]. For pixel p in year t , let $r_{\{k,p,t\}} \in [0, 1]$ be the standardised intensity for layer k . The composite disturbance at the pixel level is therefore:

$$c_{\{p,t\}} = \max_k (w_k \times r_{\{k,p,t\}})$$

While there is a risk that this approach can potentially underestimate cumulative or synergistic pressures, this choice ensures that co-located pressures do not inflate scores simply because multiple mapped layers describe the same underlying footprint; instead, the composite reflects the strongest weighted pressure at that location. Pixel-level composite values are then aggregated to each VNU cell (1 km²) for year t using summary functions appropriate to the intended interpretation (e.g., mean intensity or proportion of pixels exceeding a disturbance threshold). Where $D_{\{i,t\}} \in [0, 1]$ denotes the resulting cell-level disturbance score (e.g., the mean of $c_{\{p,t\}}$ over all pixels within cell i), HI is defined as the inverse:

$$HI_{\{i,t\}} = 1 - D_{\{i,t\}}$$

so that higher $HI_{\{i,t\}}$ indicates lower mapped anthropogenic pressure (i.e., relatively more intact habitat condition) at the annual 1 km^2 accounting scale. Project-level HI at time t can be summarised as the area-weighted mean of $HI_{\{i,t\}}$ across all VNU cells within the project boundary. Importantly, HI is computed for all cells within the defined project area regardless of legal designation; thus, pressures can occur within protected areas (e.g., roads, infrastructure, edge effects, encroachment, extraction, and altered fire regimes), while the intent of HI is to quantify these pressures transparently to support mitigation, adaptive management, and verifiable outcomes reporting within an MRV framework.

2.3. Indicator Species (IS)

Indicator species are widely used as cost-effective proxies for ecosystem condition, especially where comprehensive biodiversity inventories are infeasible [27,28,51]. However, single species rarely reflect the condition of entire ecosystems, and indicator frameworks perform best when they incorporate multiple taxa, trophic levels, and functional roles [51,52]. We therefore define 10 indicator groups representing functional guilds of conservation concern (e.g., local range-restricted or endemic taxa, large herbivores, apex carnivores, mesopredators, scavengers, habitat specialists, and other ecologically informative groups; Table S1). Grouping species into guilds improves interpretability and robustness across heterogeneous communities and reduces sensitivity to natural biogeographic variation among sites, thus the IS component is designed to infer significant directional change in ecosystem functionality, not to penalise cells simply because a particular species is naturally absent from a location.

Within each guild, one or more focal species are selected based on ecological relevance, sensitivity to anthropogenic pressures, and the availability of repeatable monitoring data. Indicators are monitored using a combination of standardised protocols (e.g., camera trap surveys, acoustic recorders, line transects, aerial surveys, and ranger-based observations), with recorded sampling effort (e.g., trap nights, recorder deployment duration, transect length, observation hours) used to support comparable inference through time and transparent auditing. To estimate temporal trends while accounting for imperfect detection, we fit dynamic occupancy models to detection–non-detection time series at the scale of sampling sites (e.g., camera stations, acoustic points, transect segments [53]). Occupancy probability for each species in each year is modelled as a function of time, with significant trend determination and segmentation over time. Detection probability is modelled separately and explicitly includes effort as a detection covariate, alongside other survey condition covariates where relevant (e.g., habitat type, season, device model), thereby reducing bias from variable sampling intensity. Bayesian estimation via Markov Chain Monte Carlo (MCMC) yields posterior distributions for annual occupancy and significant trend parameters for each species.

Species-level outputs are then aggregated at project level to generate a conservative, decision-relevant classification. For each species, we derive a posterior distribution for significant change through time (e.g., change in occupancy from baseline to the most recent monitoring year, or an estimated slope over the monitoring period), propagating uncertainty from both detection and occupancy. We classify the change as declining when there is credible evidence of decline (e.g., the 95% credible interval for change lies entirely below zero, or equivalently the posterior probability of decline exceeds a high threshold such as 0.95). Otherwise, it is classified as non-declining (i.e., stable or improving). Each species trend is assigned a score of 1 (i.e., non-declining) or 0 (i.e., declining), where the project-level IS score is calculated as:

$$IS_t = p_t/n_t$$

where p_t is the number of species with sufficient data to estimate non-declining trends in the current period, and n_t is the total number of species monitored in the current period. This normalisation helps maintain comparability over time, including when additional species and guilds are added as monitoring capacity expands. Importantly, species that are naturally absent from a cell do not automatically reduce scores; inference is based on modelled trends for the set of indicators monitored within each guild. As consistent monitoring is itself a requirement for verifiability, we track guild coverage and any absence explicitly, treating insufficient coverage as a separate eligibility criterion rather than conflating it with ecological decline.

2.4. Ecological Integrity (EI) and VNU Issuance

The approach presented in this section integrates the methodological components described and referenced in the preceding sections into an auditable unit framework designed to provide a simplified representation of EI. Although the individual components are established, their synthesis into a single auditable unit with specific issuance rules represents a novel contribution of this study.

EI scores for each potential 1 km² VNU cell integrate project-level HI and IS for each monitoring period. Change in HI is quantified for each cell relative to both the previous monitoring period and the baseline year. A cell satisfies the habitat criterion if its HI has not declined beyond pre-specified tolerance thresholds that accommodate expected remote sensing uncertainty, short-term natural variability and minor measurement noise. We specify short-term and long-term tolerance buffers of $\epsilon_{ST} = 0.05$ and $\epsilon_{LT} = 0.10$, representing permissible declines in cell-level HI between consecutive monitoring periods and between baseline and the current period, respectively. These values are transparent first-pass assumptions rather than universal ecological constants: the short-term buffer allows limited annual variation, while the long-term buffer prevents repeated small declines from being treated as acceptable indefinitely. Cells with HI declines exceeding these defined thresholds are considered ineligible for issuance in that period, and future applications should test the sensitivity of issuance outcomes to these values in different ecosystems and monitoring contexts. Change in IS are quantified at the project level and interpreted as the proportion of indicator species that are non-declining. This is translated into E_t , a project-level eligibility factor derived from IS performance. Tolerance buffers ($\epsilon_{ST} = 0.05$ and $\epsilon_{LT} = 0.10$) are applied to allowable declines: $E_{t\{ST\}}$ represents the short-term eligibility factor and $E_{t\{LT\}}$ the long-term eligibility factor. If performance declines remain within these thresholds, then $E_{t\{ST\}} = 1$ and $E_{t\{LT\}} = 1$, and therefore $E_t = 1$. If declines exceed the thresholds, each component factor is reduced proportionally to the extent to which the threshold is exceeded. The overall eligibility factor is then calculated as:

$$E_t = E_{t\{ST\}} \times E_{t\{LT\}}.$$

The number of eligible VNUs, summed across the project boundary, is calculated as the number of cells that satisfy the HI criteria multiplied by E_t . Finally, for cell i in monitoring period t , the EI score is thus defined as:

$$EI_{\{i,t\}} = 0.5 \times HI_{\{i,t\}} + 0.5 \times IS_t$$

These eligible VNUs provide the issuance quantity for outcome-based accounting and can underpin biodiversity credits, performance-based grants, or nature-linked financial instruments. For completeness, we also report project-level HI as the area-weighted mean of $HI_{\{i,t\}}$ across all cells within the project boundary, providing a structural habitat condition summary alongside cell-level eligibility outcomes.

2.5. Verification

Projects applying the VNU methodology are expected to undergo independent verification and, where there is commercial offtake or formal issuance, this should be conducted by an accredited third-party body consistent with ISO14019 [54], an emerging best practice for Earth-observation-based MRV [43,54]. Verification should include: (i) review of project design, baselines, and monitoring protocols; (ii) audit of raw data, data-processing chains, and analytical code for the HI and IS components; (iii) checks on registry records and accounting procedures to prevent double counting; and (iv) confirmation that eligibility rules and buffer thresholds have been applied consistently. For HI, auditors should confirm data provenance, sensor, and product versions, masking and pre-processing procedures (e.g., cloud and shadow screening where relevant), disturbance-layer definitions, aggregation methods, and uncertainty quantification; whereas for IS, auditors should review survey design, effort metadata, data management procedures, model specification, and diagnostics, and sensitivity analyses to key assumptions (e.g., detection heterogeneity, effort variation, and tolerance levels). Tolerance thresholds are treated as explicit, pre-specified assumptions and should be assessed during verification (e.g., via sensitivity analyses and comparison against plausible uncertainty bounds for the underlying data products) to ensure that permissible change is not conflated with true ecological change. Where outcomes are used in finance-linked instruments, registry processes should ensure traceability of issued VNUs over time and prevent double counting across claims or buyers; costs associated with conservation and restoration activities that generate the measured integrity outcomes should be documented to enhance transparency and support assessments of cost effectiveness. By embedding these verification requirements, the VNU framework is designed to be sufficiently pragmatic and robust for use in contractual arrangements, regulatory disclosure and nature-linked financial products. In the MWR case study presented here, the data-processing and eligibility steps are demonstrated, but full third-party verification had not been completed at the time of manuscript preparation. We therefore treat verification as a core methodological requirement and an explicit limitation of the current case study, rather than as an empirically demonstrated result.

3. Results

To demonstrate real-world implementation, we applied the VNU framework to MWR in southern Malawi. It is presented here as a case study illustrating the outputs directly generated by the proposed methodological framework and describing the results for the individual components (HI and IS), as well as the composite EI score and VNU issuance eligibility.

The reserve boundary intersected 711 VNU cells (1 km²), defining the maximum potential issuance for the site. HI was assessed annually relative to a fixed 2018 baseline through 2024/5, and IS performance was assessed over 2021–2025. MWR was selected as a proof-of-concept and workflow demonstration in a high-integrity, relatively stable system. It is therefore a favourable-case implementation test, not a full stress test of the framework across strongly degraded or highly heterogeneous landscapes.

3.1. Habitat Intactness (HI)

MWR habitats remained highly intact across the assessment window, with disturbance signals spatially localised and dominated by necessary conservation support infrastructure developments (e.g., internal gravel roads and ranger posts) and associated limited, localised vegetation clearance rather than broad land conversion (Figure 2). No cropland was detected within the reserve boundary during the assessment period, though this change was evident in the surrounding landscape. Mean HI remained ≥ 0.99 at both baseline (2018)

and the most recent assessment year (2024/5). Applying the long-term tolerance rule, no VNU cells exceeded the allowable decline relative to baseline.

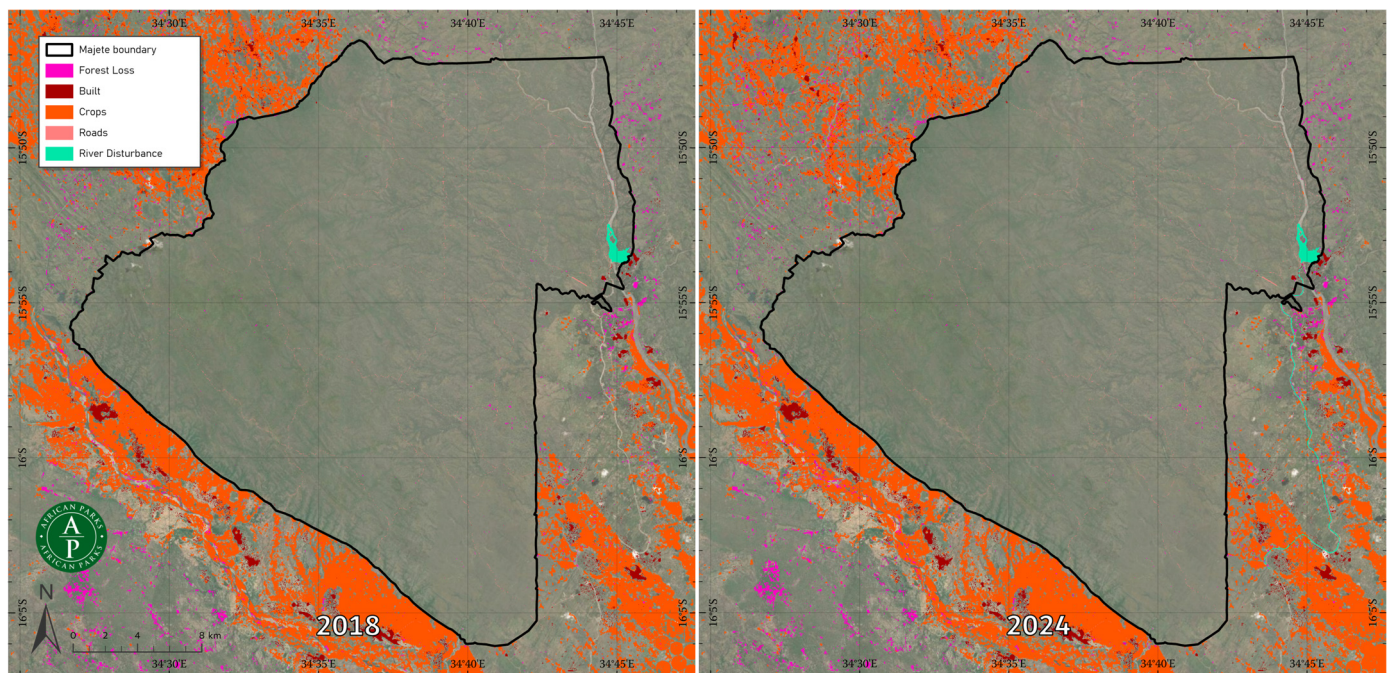


Figure 2. Spatial distribution of consolidated disturbance layers used to estimate habitat intactness (HI) for Majete Wildlife Reserve (MWR), Malawi. Maps show the project boundary (i.e., black outline) overlaid on the 1 km² VNU grid and the harmonised disturbance inputs for the baseline year (i.e., 2018; left) and the most recent assessment year (i.e., 2024; right). Disturbance classes comprise built infrastructure, roads, cropland, forest loss and river disturbance, aggregated from native-resolution datasets to the 1 km² accounting grid and combined using the weighted composite disturbance formulation before transformation to HI. The figure illustrates that disturbance signals are largely concentrated along infrastructure corridors and boundary-adjacent areas, with limited evidence of broad land conversion within the reserve interior. Surrounding areas are shown for context to illustrate pressure gradients; however, VNU issuance is based on temporal change within the project boundary relative to its own baseline (self-referential), not on comparisons with adjacent landscapes.

3.2. Indicator Species (IS)

Detection-corrected occupancy scores for six indicator species across four functional groups (i.e., ‘Vulnerable’: *Acinonyx jubatus* and *Lycan pictus*; ‘Keystone/Engineer’: *Diceros bicornis* and *Loxodonta africana*; ‘Large carnivore’: *Panthera leo*; and ‘Large herbivore’: *Giraffa camelopardalis*) revealed high and maintained park-level occupancy (ψ) throughout 2021–2025 (Figure 3). Across groups, estimated occupancy probabilities were generally in the ~65–75% range. ‘Keystone/Engineer’, ‘Large Carnivore’ and ‘Large Herbivore’ groups exhibited a short-lived peak in 2023 (~72–75%) followed by a return toward ~65–70% in 2024–2025, while the Vulnerable group remained stable (~66–67%) across the full time series. Uncertainty widened in some periods, most notably for the ‘Keystone/Engineer’ group in 2024, but credible intervals broadly overlapped across years, and the segmented trend fits did not indicate a persistent decline in any group over the assessment window.

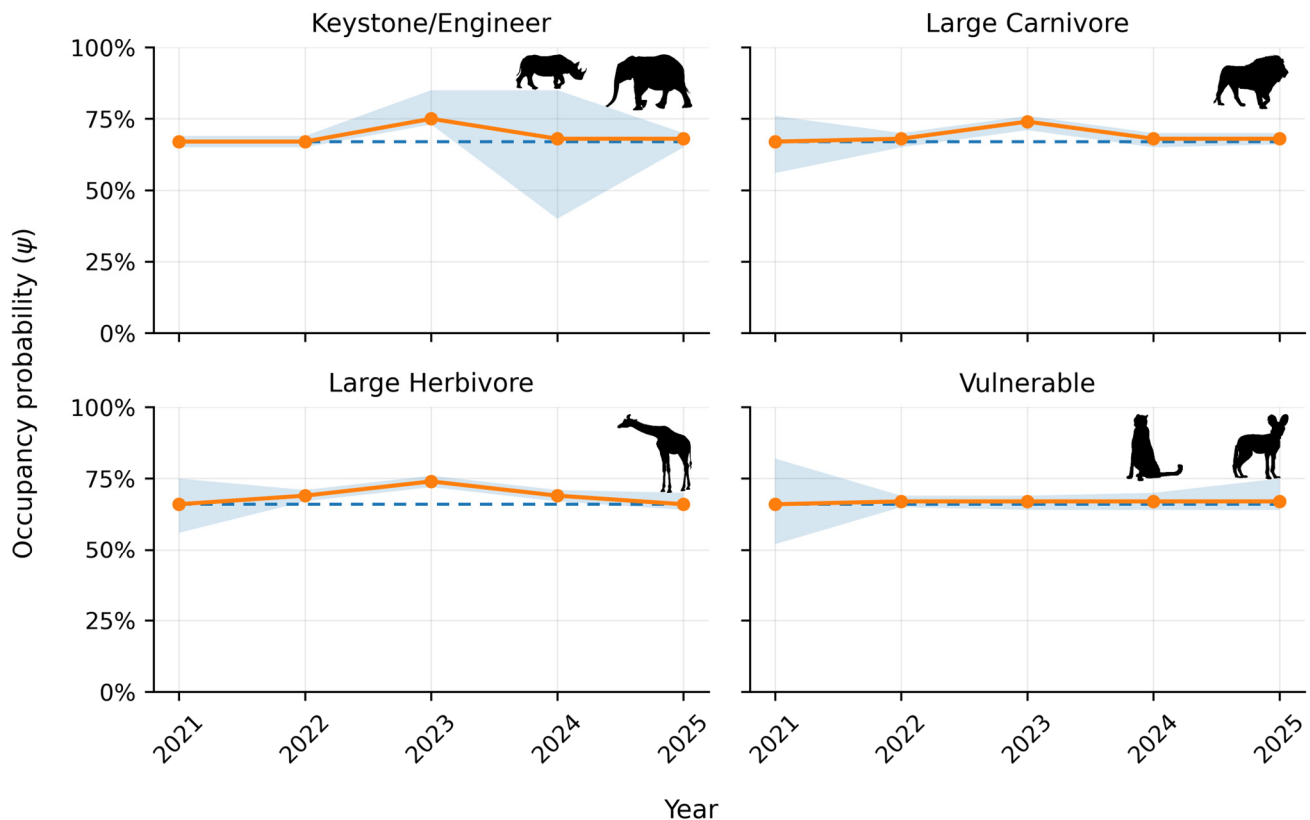


Figure 3. Functional-group trends in indicator species occupancy (ψ) for Majete Wildlife Reserve (MWR), Malawi (2021–2025), estimated using segmented regression within a dynamic occupancy framework. Panels show annual occupancy probability (i.e., ψ ; solid line with points) derived from detection–non-detection monitoring data using dynamic occupancy models that account for imperfect detection, aggregated to four functional indicator groups: Keystone/Engineer, Large Carnivore, Large Herbivore, and Vulnerable. Shaded ribbons denote 95% credible intervals around annual estimates. Dashed lines show the fitted segmented (piecewise) regression through time (i.e., segmented trend fits), allowing changes in slope where supported by the data. Across groups, occupancy remained broadly stable over the monitoring window, with short-lived increases around 2023 for several groups and wider uncertainty in some periods, but no evidence of sustained group-level decline under the decision rules used for issuance eligibility.

3.3. Ecological Integrity (EI) and VNU Issuance

Combining cell-level HI with the project-level IS eligibility factor yielded an overall EI score of 0.99 for the 2024/5 assessment period, with an HI score of ≥ 0.99 (i.e., habitats remained highly intact across the assessment window) and IS score of 1.0 (i.e., all assessed functional groups classified as non-declining; $E_t = 1$). Following VNU eligibility standards, all 711 cells satisfied both the HI and IS criteria and were therefore eligible for VNU issuance in the 2024/5 assessment period. This issuance result should be interpreted as a methodological output from the case study workflow; formal third-party verification was not empirically included because it had not yet been finalised at the time of publication.

4. Discussion

This study set out to demonstrate how ecological integrity can be translated into a nature-financing-ready unit that is measurable, comparable, and verifiable at the project scale. We developed the VNU as an outcome-based MRV framework that integrates (i) habitat intactness derived from spatial disturbance layers and (ii) indicator species performance derived from standardised field monitoring, producing a unit that can be issued only when integrity is maintained or improved. In doing so, we respond directly

to the widely recognised mismatch between accelerating biodiversity loss, the scale of the conservation finance gap, and the limited availability of robust, decision-relevant integrity measures that can function in contracts and financing instruments [9,19,55]. The key finding from the MWR use case is that the VNU workflow can be implemented with transparent rules and auditable inputs, producing clear eligibility outcomes that can, in principle, trigger finance disbursement and accountability mechanisms. This establishes the basis for considering where, and under what conditions, VNUs may be most useful in real-world protected-area and landscape financing, particularly where managers need credible, spatially explicit evidence of land condition and ecological performance.

Successful application of the VNU framework in MWR illustrates both its feasibility and its limits. MWR has transitioned from severe depletion to a well-managed and seemingly ecologically stable state, making it an informative but favourable test case rather than evidence that all parameter choices will perform equally well in more complex landscapes. The site is useful precisely because it allows the full workflow to be demonstrated against a traceable monitoring system and a relatively clear management history (e.g., [39,40]). The method supports project-scale interpretation by linking spatially explicit changes in mapped anthropogenic pressure (HI) with indicator guild (IS) trajectories, returning an issuance decision that is clear enough to communicate to managers and stakeholders while remaining grounded in auditable evidence streams. Importantly, while this case study is situated within a protected area and reflects the available monitoring system, the underlying logic is transferable to other project contexts where outcome-based finance hinges on demonstrable change and credible verification (e.g., conservancies, restoration concessions, and watershed/source-area projects), provided that input data, monitoring effort and governance arrangements can support consistent reporting and independent audit. In systems that are degrading, VNU issuance is expected to reduce or halt when HI falls beyond tolerance thresholds and/or indicator guilds show credible and consistent decline. In heterogeneous landscapes, where patterns of recovery and degradation coexist, the cell-level structure of VNUs enables spatially explicit differentiation, allowing areas of stability or improvement to remain eligible while others are excluded, incentivising nature as a land use where possible and supporting targeted management responses. In cases of conflicting ecological signals (e.g., herbivore population increase driven by predator decline), the use of multiple, diverse guilds provides a balancing mechanism; however, such cases should also trigger closer ecological interpretation rather than a purely mechanical issuance decision.

The principal methodological contribution of the MWR case study is to provide a practical bridge from existing, fragmented integrity proxies to a standardisable, transaction-ready unit, while explicitly acknowledging that key assumptions remain. Overall integrity metrics are valuable for conservation prioritisation and landscape- to national-scale status reporting, but they can be poorly matched to project-level decision-making because they rely on coarse-resolution datasets, pooled model assumptions, and limited local adaptability [20,22]. The VNU approach is therefore designed to complement, rather than replace, broader ecological integrity assessment frameworks by retaining fine-grain spatial attribution (i.e., cell-level outcomes) and pairing remote sensing with ecoregion- and project-relevant species monitoring.

Importantly, it is not proposed here as a one-stop or exhaustive measure of ecological integrity. Ecological integrity is inherently scale-dependent and is influenced not only by local habitat condition and indicator guild trajectories, but also by protected-area size, connectivity to surrounding landscapes, edge effects, disturbance regimes, trophic interactions, life history traits, and emergent functional processes that may not be fully captured by a 1 km² annual accounting unit. Remote sensing can also miss subtle or cryp-

tic disturbances (e.g., under-canopy degradation and selective impacts), while indicator monitoring depends on careful methodological selection and consistent effort to preserve species comparability over time [15,56]. Accordingly, the value of the VNU lies not in claiming ecological completeness but in providing a practical and auditable entry point through which protected and conserved areas can evidence stewardship performance, access outcome-linked finance, and build the monitoring infrastructure needed for progressively more nuanced assessments. Given that EI is realised and managed within sustainable social–ecological systems, where institutions, livelihoods and historical context shape both pressures and responses, applications of the VNU should explicitly document relevant safeguards and co-benefits. Where appropriate, they should also incorporate standardised socio-economic metrics aligned to the finance instrument and due-diligence requirements, including those relevant to Indigenous Peoples and local communities [1,24].

By combining indicator guilds with spatially mapped anthropogenic pressures, the VNU provides a pragmatic route to ‘valorising’ natural capital as a measurable outcome unit that can support land stewardship and multiple financing use cases. A core barrier identified by financial authorities and emerging disclosure frameworks is the lack of robust, comparable, decision-grade measures of nature performance that can be embedded in instruments and oversight at the level where transactions occur [55,57]. VNUs are intended to reduce this friction by making outcomes legible; for example, units could support outcome-based philanthropic grants, biodiversity/nature crediting (i.e., where standards permit), performance-based trust fund disbursements, nature-linked loans or bond structures, and, in some contexts, public payment schemes for ecosystem services. This matters because even promising conservation finance mechanisms, including debt-for-nature swaps, repeatedly confront complexity (e.g., legal structuring and contracting, baseline/eligibility definition, MRV design and verification, and registry/claims management), negotiation and monitoring costs, and credibility constraints that limit replicability; constraints that stronger, standardised MRV can help to reduce, while still requiring careful governance and equity design [58,59]. This positions the VNU not only as a project tool, but as a potential building block for policy-aligned nature finance at scale.

The broader policy contribution is to offer an operational ‘unit of account’ concept that aligns local ecological outcomes with the current trajectory in global biodiversity policy and nature-related financial governance. The Kunming–Montreal Global Biodiversity Framework calls for transforming incentives, scaling finance, and improving monitoring and accountability for biodiversity outcomes [19], while major economic and financial assessments increasingly emphasise that nature degradation is financially material yet hindered by data and metric gaps [16,55,60]. The VNU approach provides a concrete pathway for bridging these agendas through a transparent MRV workflow that can be implemented in data-constrained settings, verified against clear rules, and iterated as indicator databases expand, automation improves, marine and further freshwater integrity components are added, and social safeguards are standardised alongside ecological outcomes [1,56,57]. In this way, the VNU contributes towards addressing challenges related to biodiversity loss, natural capital, and the finance gap, by showing how integrity outcomes can be made investable without abandoning ecological nuance or social legitimacy.

5. Conclusions

For conservation finance to scale, it must move beyond reporting inputs and activities (e.g., area managed, patrol effort, or hectares treated) to rewarding demonstrated ecological outcomes. In this study, we propose the VNU as a practical, outcome-based MRV framework that approximates changes in ecological integrity at 1 km² resolution by combining a disturbance-based HI component with an IS component derived from repeated moni-

toring of functional guilds, alongside defined eligibility and verification rules. The main contribution of the VNU lies in the integration of these established elements into a single, transparent, and auditable framework that supports nature finance mechanisms. The approach is deliberately pragmatic: it does not claim to measure biodiversity or ecological integrity exhaustively but instead provides a consistent accounting structure through which ecological outcomes can be reported, audited and linked to financial instruments. In doing so, it strengthens incentive structures for long-term nature stewardship and contributes to the advancement of outcome-based financing approaches in support of global biodiversity goals, while offering a scalable framework that can be applied across diverse landscapes.

The MWR case study operationalises the framework by demonstrating how the VNU workflow can be implemented using existing spatial and ecological monitoring datasets. Across 711 potential VNU cells, HI remained high (≥ 0.99) from 2018–2024/5, indicator guild occupancy remained high and non-declining over 2021–2025, and all cells were therefore eligible for issuance under the specified decision rules. These results practically demonstrate how protected and conserved areas can translate monitored habitat condition and species response information into a clear, spatially explicit performance outcome that can be independently verified and converted into standardised accounting units. This provides a robust basis to underpin outcome-based nature financing mechanisms, including grants, biodiversity credits, nature-linked bonds and other natural-capital instruments, by linking ecological outcomes to financial incentives.

The main limitations are equally important to consider. The MWR case study represents a high-integrity and relatively stable system, so it does not fully test framework performance under strong degradation, conflicting indicator responses, complex land use mosaics or weak monitoring coverage. The tolerance buffers and pressure weights are explicit assumptions, not settled ecological constants, and full third-party verification was not empirically demonstrated for this case study.

Future research and pilot implementation should therefore focus on sensitivity testing, independent verification readiness, stronger uncertainty reporting, protected-area size and connectivity effects, additional functional indicators, social safeguard metrics, and applications across more degraded, heterogeneous and biome-diverse landscapes. Similar applications now underway in Odzala–Kokoua National Park (Republic of the Congo), Garamba National Park (DRC), and Zakouma National Park (Chad) should be treated as method refinement opportunities before broader finance-ready use.

Supplementary Materials: The following supporting information can be downloaded at: <https://www.mdpi.com/article/10.3390/land15071305/s1>, Table S1. The 10 indicator species groups. The presence of at least one species per group indicates the highest ecological integrity. Species are selected per ecoregion. Illustrations of species from BioRender and Birds of the World; Table S2. Weights for different disturbance layers. The disturbance layers and associated weights are adapted from the Human Footprint framework and related human-pressure-mapping literature [11,45–48]. Rationale descriptions were refined and expanded, also informed by expert opinion. Refs. [61–64] are cited in the Supplementary Materials.

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Data Availability Statement: Case study data can be made available upon reasonable request through the corresponding author.

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