Ecosystem condition assessments: A context-specific workflow to integrate local expert knowledge and remote sensing

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Abstract

Despite decades of conservation science, we still struggle with a deceptively simple question: how do we know if an ecosystem is in good or poor condition? We present a reproducible, six-step workflow for assessing ecosystem condition using remote sensing, ecological knowledge, and expert validation. The approach is designed to be applied consistently across diverse biomes, while remaining sensitive to ecosystem-specific dynamics. It suggests steps for the detection of gradual changes in ecosystem condition driven by key pressures such as livestock farming and ranching, invasive species, or altered disturbance regimes, that traditional land cover classifications may miss. We demonstrate the workflow in Albany Thicket vegetation (South Africa) using high-dimensional satellite embeddings and a deviation-from-reference approach, capturing spatial gradients in ecosystem condition consistent with known degradation patterns and enabling continuous mapping for conservation and restoration planning and prioritization. By integrating expert input with scalable remote sensing metrics, the workflow provides ecologically meaningful and policy-relevant outputs. Importantly, it is aligned with both the IUCN Red List of Ecosystems and UN System of Environmental-Economic Accounting Ecosystem Accounting, thereby bridging two global standards and supporting national reporting towards the Kunming-Montreal Global Biodiversity Framework and Land Degradation Neutrality targets. This operational framework offers a transparent, adaptable, locally relevant and globally comparable approach for assessing ecosystem condition along a continuum of change, strengthening the evidence base for conservation, restoration, and emerging biodiversity markets.

Introduction

Ecosystem condition assessments have become an important tool in conservation and restoration planning, to determine the state, functioning and integrity of biodiversity (Thomas et al., 2025), yet they face fundamental challenges because ecosystems operate across multiple scales, change constantly, and there are no universal benchmarks of "health". By identifying patterns of degradation or resilience, ecosystem condition assessments help identify threats, guide conservation and restoration priorities, and establish baselines for long-term monitoring (Jakobsson et al., 2021; Kokkoris et al., 2025). Ecosystem condition assessments are also critical for reporting on national and international biodiversity targets, such as the Kunming–Montreal Global Biodiversity Framework (GBF) and Land Degradation Neutrality (LDN) goals (Nicholson et al., 2021). The rapidly growing carbon and biodiversity credit markets (Wunder et al., 2025) create additional urgency for context-specific, but reproducible and scalable, assessment approaches. Although ecological condition assessments can be made at any spatial scale, from small restoration sites to biomes, they require clearly defined spatial ecological units and typologies, making scale and extent central to both interpretation and implementation (Kokkoris et al., 2025). This paper proposes a reproducible, remote sensing-based workflow for assessing ecological condition across spatial scales.

Intergovernmental organizations have sought to standardize how ecosystems are classified and delineated to support assessments of ecosystem loss and degradation (Bagstad et al., 2025). Two complementary global standards, the International Union for Conservation of Nature (IUCN) Red List of Ecosystems (RLE; Keith et al., 2013) and United Nations System of Environmental-Economic Accounting Ecosystem Accounting (SEEA EA; Edens et al. 2022), provide internationally recognized frameworks for recording and interpreting changes to ecosystems. Both rely on the IUCN Global Ecosystem Typology (GET; Keith et al., 2020) as their foundational ecosystem classification and for its maps (Xiao et al., 2024). The GET classifies ecosystem types hierarchically, based on shared ecological processes, environmental drivers, and/or characteristic biota, with level 5 in the hierarchy representing regional ecosystem types and the lowest, level 6, delineating more fine-scaled ecological communities (Keith et al., 2020). The RLE assesses biodiversity loss of ecosystems by quantifying the risk of ecosystem collapse (IUCN, 2024), whereas the SEEA EA associates ecosystem change with the services provided to the economy or people (Edens et al., 2022). Both serve as headline indicators for the GBF for national and global reporting, with South Africa being a pioneer in implementing both standards (Botts et al., 2020; Xiao et al., 2024). In the RLE, ecosystem condition is operationalized via Criteria C (environmental degradation) and D (disruption of biotic processes), which assess the severity and extent of degradation relative to "collapse thresholds" (IUCN, 2024). These criteria are central to risk classification but are applied less often than extent-based assessments (Skowno & Monyeki, 2021). In SEEA EA, ecosystem condition accounts record selected biophysical characteristics of ecosystems through time, typically relative to a reference condition, which provides the bridge between extent and ecosystem services accounts (Edens et al., 2022). Therefore, while both the RLE and SEEA EA explicitly recommend and/or require ecosystem condition data to accurately assess the state of ecosystems, in practice it is rarely included (Maes et al., 2020; Xiao et al., 2024). A clear research gap is the absence of a reproducible workflow for assessing ecosystem condition that is transferable across ecosystems and reporting frameworks.

Following Keith et al. (2020), who expanded on the SEEA EA definition of ecosystem condition, we define ecosystem condition as the "quality of an ecosystem that may reflect multiple values, measured in terms of its abiotic and biotic characteristics across a range of temporal and spatial scales. Quality is assessed with respect to ecosystem structure, function and composition, which underpin the ecological integrity of the ecosystem". Abiotic condition variables capture the physical and chemical environment that constrains ecological processes (e.g., soil moisture, salinity, pH, temperature regimes, hydroperiod, groundwater depth). Biotic components can be assessed through composition measures, such as species presence, abundance or richness. For example, the Biodiversity Intactness Index provides a measure of ecosystem condition using the average abundance of organisms (Clements et al., 2024). Structure (vegetation biomass or density) and function (e.g., productivity or decomposition; Edens et al., 2022), can also be used to assess the biotic components. Here we view ecosystem condition from an intrinsic, ecocentric perspective (Keith et al., 2020), along a gradient from intact to fully transformed ecosystems. "Intact" refers to an ecosystem that is abiotically, compositionally, structurally and functionally close to a reference that has been minimally modified by human activities.

Assessing ecosystem condition at the national scale requires methods that are repeatable, consistent, spatially explicit and comparable across biomes. Remote sensing (RS) offers a powerful and cost-effective tool for assessments across large spatial and temporal scales, especially in inaccessible regions and resource-constrained countries, such as South Africa (Pettorelli et al., 2016). Satellite-based sensors capture data on land surface properties, e.g. vegetation greenness, soil exposure or canopy height, that serve as proxies for ecological characteristics such as vegetation cover or biomass (Cardoso et al., 2025). Additional benefits include retrospective analyses using time series (albeit for only as far back as RS data are available), and wall-to-wall coverage of ecosystem types or biomes (Murray et al., 2018). However, challenges remain. RS-derived variables are proxies of ecological condition, requiring careful interpretation by ecologists. Many ecological characteristics, such as species composition or soil health, remain challenging to capture with RS (Kennedy et al., 2014). Operational limitations, such as cloud cover, and methodological choices introduce uncertainty in derived metrics (Lark et al., 2022). Advances in statistical modelling, time-series smoothing, and data fusion techniques (Sengani et al., 2023) have helped reduce these uncertainties (Lark et al., 2022), but field-based observations remain essential for calibrating and verifying remotely sensed indicators against on-the-ground ecological reality (Cardoso et al., 2025). Critically, RS approaches to ecosystem condition mapping should begin with input from local experts to identify key drivers of condition, indicator variables, reference states and collapse pathways. The expert knowledge anchors the choices of RS approaches and provides reference and training sites for RS approaches (Thompson et al., 2009). Therefore, RS provides an approach to scale up the local expert-derived insights to the landscape level by repeatedly measuring condition variables against explicit reference conditions within accounting and risk frameworks.

Spatial ecosystem condition assessments are generally approached in two ways: i) mapping the key pressures that drive ecosystem change (Luo et al., 2024), e.g. cropland extent, or ii) directly measuring the composition, structure and function of ecosystems (e.g. Clements et al., 2026). Each approach has intrinsic challenges when using RS data to measure condition, because satellite proxies rarely align perfectly with on-the-ground pressures or with biotic state variables, underscoring the need for careful interpretation and field calibration (Murray et al., 2018). Many available spatial datasets or products intended to capture composition, structure or function to assess ecosystem condition, are not tailored to any given ecosystem type (see e.g. Thomas et al., 2025). Others attempt to map many pressures simultaneously (e.g., Global Human Modification; Theobald et al., 2025), but these cumulative layers are not ecosystem-specific and may be less informative for diagnosing change pathways resulting from individual pressures. Context-specific ecosystem condition assessments require a hybrid approach which enables the selection of indicators that directly reflect ecosystem-specific degradation pathways to quantify both the severity and extent of degradation, two requirements that are needed for the RLE assessments and not readily met by generic pressure or global condition products. Therefore, we must first identify the key pressures of an ecosystem and then the structural, composition and/or functional components that may both respond to the key pressures and be measured with satellite data.

This paper describes a reproducible, expert-guided RS-based workflow for assessing ecosystem condition across different biomes. We illustrate the workflow with a case study in the Albany Thicket biome in South Africa. This case study evaluates the workflow under the relatively favorable conditions of structurally stable, evergreen ecosystems subject to a well-characterized dominant pressure. In doing so, the study establishes the potential of the approach, but also its constraints, particularly in more dynamic biomes. Unlike conventional satellite-derived approaches that rely primarily on categorical land cover change (Kgaphola et al., 2023; Seymour et al., 2025), our workflow is designed to detect subtle degradation within natural land cover classes, a gap identified in both biodiversity monitoring and ecosystem accounting efforts (Czucz et al., 2021; Jakobsson et al., 2021). This work builds on decades of degradation and spatial ecological condition research undertaken in southern Africa (Bell et al., 2023; Dube et al., 2017; Hoffman & Todd, 2000; Lloyd et al., 2002; Meadows & Hoffman, 2002; Milton et al., 1998; Palmer & Bennett, 2013; Thompson et al., 2009; Wessels et al., 2007). We structure the workflow in six steps, described below.

Methods

In South Africa, a megadiverse country (Mittermeier et al., 1999), comprising nine biomes shaped by distinct abiotic and biotic processes, complex ecological interactions and diverse drivers of change make comparable ecosystem condition assessments difficult (Rouget et al., 2006). South Africa assesses risk of ecosystem collapse using the RLE approach by analyzing the distribution and remaining extent of ecosystem types (Skowno & Monyeki, 2021). The National Vegetation Map (NVM; Mucina & Rutherford, 2006) is used as the historical extent of ecosystems, together with the South African National Land Cover (SANLC) products (DFFE, 2024) to calculate remaining extent of ecosystems. Although land cover data may accurately assess habitat loss, e.g., from grassland to cropland, assessments have generally failed to quantify ecosystem condition or degradation within natural remnants across much of South Africa (Skowno & Monyeki, 2021). This stems from data deficiencies and resource constraints that prevent field-based assessments of ecosystem condition. Consequently, although initial steps to include ecosystem condition in RLE assessments have been taken (e.g. for invasive alien plant impacts), critical gaps remain. No clear workflows exist for understanding past and ongoing changes in functional, composition and structural integrity of ecosystems. This section thus outlines a workflow for assessing ecosystem condition in any biome using remote sensing and expert input (Fig. 1). The steps draw on international best practices, with Arid Thicket in the Albany Thicket biome in South Africa as a proof-of-concept. A more detailed application of this workflow for the entire Albany Thicket biome, including full methods, validation and results, is described in van der Merwe et al. (in prep.).

Because open access remote sensing data at the resolution required to detect species composition is still in its infancy (Cardoso et al., 2025), this approach focuses on vegetation structure and function. The workflow is designed to support applications aligned with the RLE, with emphasis on Criteria C (environmental degradation) and D (biotic disruption) of the RLE (IUCN, 2024), although there are many other uses for the resulting condition data. The workflow aims to quantify the severity and extent of degradation in each ecosystem being assessed.

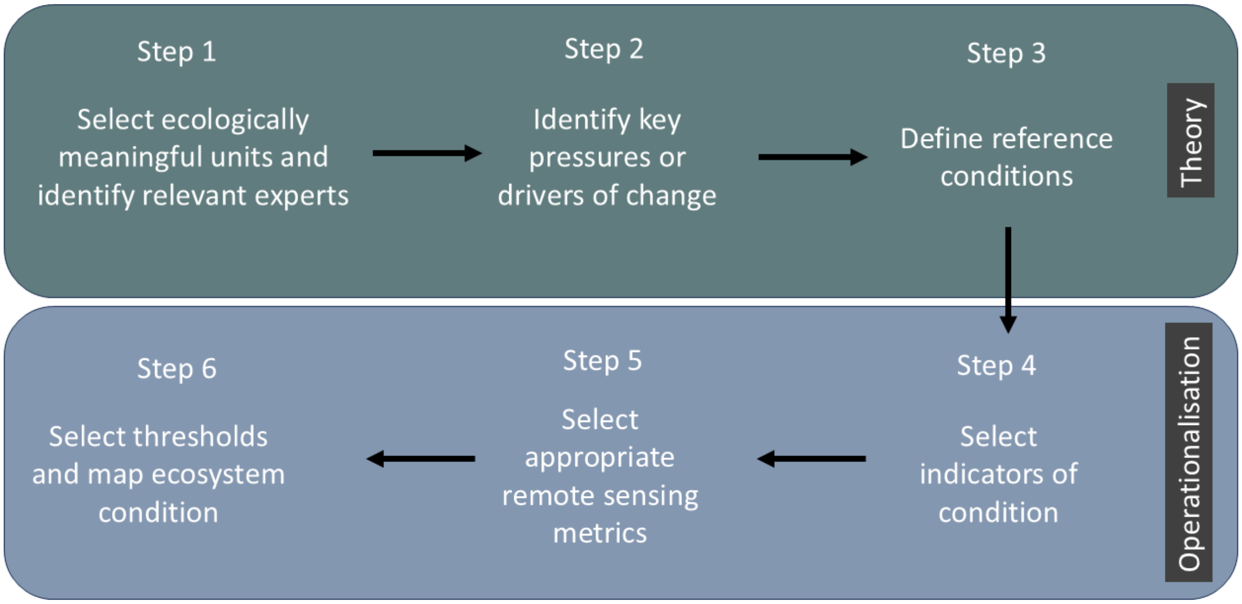

Figure 1. The ecosystem condition assessment workflow used to operationalize ecosystem condition mapping using remote sensing data together with expert knowledge, starting with ecological theoretical steps first. Steps are described in full in the main text.

Step 1: Identify relevant experts and select ecologically meaningful assessment units

The first step is to identify relevant local experts to assist in the selection of ecologically meaningful assessment units. Here, we recommend following the standards and procedures for expert elicitation provided in the RLE guidelines (IUCN, 2024). Experts are typically ecologists who hold ecosystem-specific general ecological knowledge, ideally with some experience with RS, and must co-define the change drivers, reference states, and indicators of ecosystem condition, and supply or validate training data so that the remote-sensing metrics and models target defensible ecological mechanisms.

Effective ecosystem condition assessments require both (i) an ecologically meaningful typology of assessment units and (ii) a spatial map of those units (their current and/or potential extent). Defining these units *a priori* is critical because it provides a consistent framework to delineate and describe the area of interest and forms the basis for interpreting ecological metrics in a meaningful way (Skowno & Monyeki, 2021). In South Africa, the NVM provides both a terrestrial ecosystem typology and a mapped representation of potential ecosystem extent (Mucina & Rutherford, 2006). For ecosystem condition and risk assessments, it is typically cross-tabulated with land-cover data to represent remaining natural ecosystems and transformed areas (Skowno et al., 2021). The NVM is iteratively updated and refined (Dayaram et al., 2019), and serves as a representation of the potential extent of vegetation types (pre-1750). This provides a foundation for understanding the form and function of South African landscapes and its ecological processes, as well as a baseline for detecting ecological change (Dayaram et al., 2019). The vegetation types in the NVM are used interchangeably as ecosystem types, since vegetation types were classified not only based on their floristics but also on their abiotic conditions, such as geology, soil type and climate (Mucina & Rutherford 2006). These ecosystem types can intuitively be cross-referenced to the GET ecosystem types (Keith et al., 2020) with ecosystems being nested within broader-level biomes that correspond to specific geographic space. For countries without a national ecosystem classification system, the GET provides an ideal starting point as the typology for this workflow (see e.g. Wells et al., 2025). Where a national map is lacking, assessments should either develop a defensible local map of units (via expert-led delineation and/or RS classification) or use emerging global products (e.g., the Global Ecosystem Atlas) where available.

Step 2: Identify key pressures and drivers of change

A central challenge in ecosystem condition assessments lies in identifying the key ecological characteristics and indicators that adequately reflect the fundamental processes underpinning ecosystem integrity and its change (Czucz et al., 2021). Since there are several potential indicators that may be used to define "reference ecosystem condition" in the next step, we prioritize the most relevant indicators by identifying those that are known to respond to key pressures in each ecosystem. This critical step should thus identify the key pressures driving ecological change and then focus on the biotic or abiotic aspects that may respond to these pressures. The practical starting point is the systematic identification of relevant pressures. The IUCN Threats Classification Scheme provides a comprehensive list of threats (here called pressures) that can be used for screening pressures that are applicable or not in each ecosystem. Notably, in South Africa the SANLC or other global land cover products already capture outright transformation by the key habitat loss drivers: crop production, urban development, plantations and mining (Skowno et al., 2021; Fig. 2). The approach presented here targets often more subtle degradation within natural land cover classes, such as in rangelands, which are typically driven by land use and other global change drivers such as livestock management regimes, invasive species, altered fire regimes, and climate change (von Maltitz et al., 2024). The goal is to identify degradation gradients that alter ecosystems from reference conditions. Thereafter, indicators can be chosen that may be measured with RS data, such as livestock-driven changes in plant cover.

This step uses existing peer-reviewed literature and ecosystem-specific or biome-specific expert consultations to evaluate the importance of each pressure within each assessment unit. As a foundation for ecosystem condition assessments following this workflow in South Africa, the authors of this paper, which include a broad range of ecologists, conducted an extensive review of the literature and scored the key pressures in each biome (Fig. 2; Appendix S2: Table S1). Because pressures differ in each biome, with Grassland, Indian Ocean Coastal Belt and Fynbos being the most impacted biomes in South Africa (Fig. 2), this is a critical step for the indicator and metric selection steps.

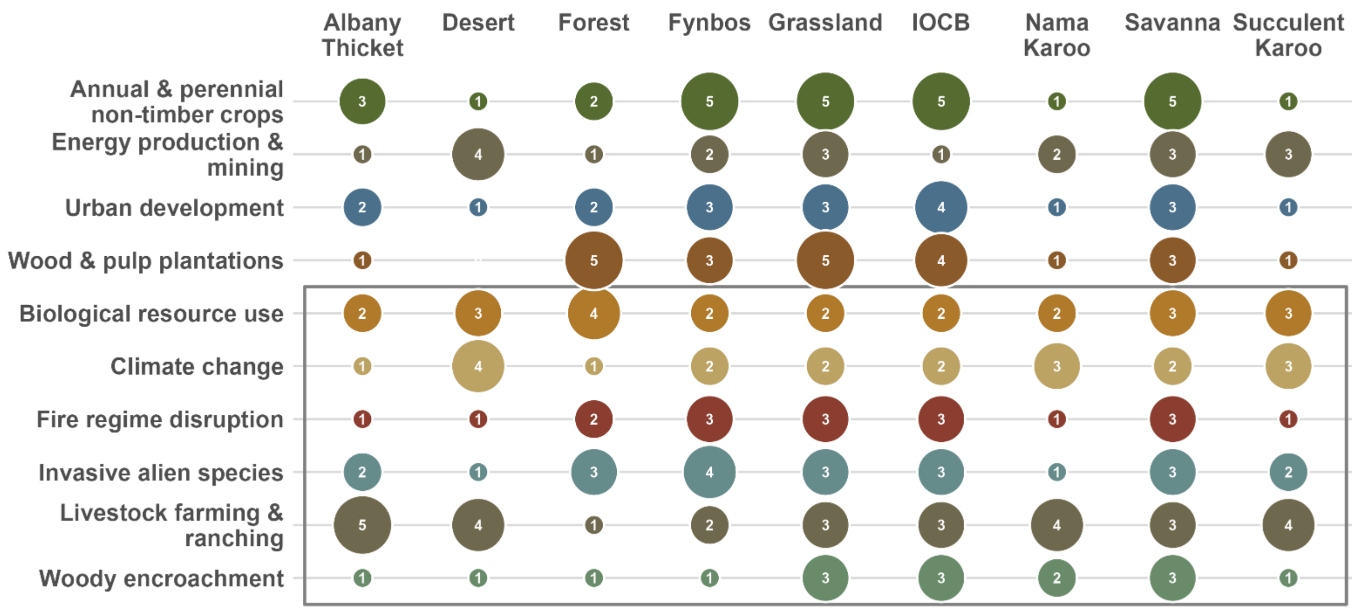

Figure 2. Key pressures per biome in South Africa, summarized from the full list of pressures in the IUCN Threat Classification Scheme (Appendix S2: Table S1), which includes both historical and present pressures. The top rows represent pressures that can already be measured using national land cover products, while the remaining categories, highlighted by the grey box, still require dedicated data development. Pressures were scored from zero to five, where five represents the most severe impact relative to extent and severity within each biome, while zero indicates the pressure is not present in the biome. Scores are intended as a first-pass, biome-level synthesis. Pressures can vary among ecosystem types or bioregions within a biome. IOCB: Indian Ocean Coastal Belt.

Step 3: Define reference ecological condition

Without clear benchmarks, condition assessment becomes arbitrary. The reference states provide a clear ecological baseline from which deviation can be measured (Gann et al., 2019). This step aligns with the SEEA EA and RLE requirements for reference states to assess ecosystem condition and risk of ecosystem collapse. The RLE, for example, uses historical or minimally disturbed baselines to assess change in biotic and abiotic features (criteria C and D; IUCN, 2024), while SEEA EA defines ecosystem condition relative to a reference that reflects a sustainable long-term average (Czucz et al., 2021; Xiao et al., 2024). Our workflow directly incorporates this principle by requiring expert-led definitions and identification of sites for reference or "intact" condition early in the assessment process (Step 2 and 3), ensuring that indicators of ecosystem condition respond to key pressures and are thus ecologically meaningful, as well as scalable, and policy-aligned. Within a risk-based assessment framework, the precise delineation between "intact"/ "natural" and "semi-natural" states is of secondary importance, as the primary objective is to quantify trajectories of degradation and identify ecosystems approaching thresholds of collapse rather than resolve fine-scale distinctions along the upper end of the condition continuum.

The location of intact sites will be used in later stages of the workflow. These reference sites should reflect the structure, composition, and function of a healthy ecosystem prior to significant anthropogenic disturbance (Durbecq et al., 2020; Edens et al., 2022; Gann et al., 2019). Expert-guided selection, ground validation, and documentation of the ecological justification for each site or reference state are recommended. We also recommend defining and describing the intact ecosystem condition similar to the GET descriptions (Appendix S1). Most ecosystems are dynamic and vary substantially with natural disturbance regimes and cycles (e.g., post-fire recovery, rainfall seasonality). Therefore, to avoid conflating natural fluctuation with degradation, reference datasets should be selected to capture the expected range of variability in intact sites by sampling across natural environmental gradients, using multi-year time series and/or disturbance-aware indicators in the next steps (see e.g., Slingsby et al., 2020). These reference sites align with the requirements of both the RLE (for defining thresholds of collapse) and SEEA EA (for setting condition baselines relative to a long-term sustainable state; Edens et al. 2022).

Step 4: Select ecosystem-specific indicators of condition

Selecting indicators is a key design step of spatial condition assessments (Rowland et al., 2018). This step translates ecological understanding (how and why ecosystems change) into variables that can be measured, interpreted and validated (Thomas et al., 2025). The guiding questions are "what changes occur in an ecosystem when it degrades?" and "can we detect these changes with RS?". Numerous studies provide guidance for indicator selection (Kairis et al., 2014; Rowland et al., 2018; Czucz et al., 2021). We therefore do not prescribe indicators here but rather include the main considerations when selecting indicators for each unit (see Appendix S2: Table S2). Because most ecosystem condition attributes cannot be measured directly with RS data, indicators should be chosen to represent observable aspects of ecosystem composition, structure, and/or function. Ideally, indicators should (1) link to one or more key pressures identified in Step 2; (2) respond to a change in state (e.g., decline with degradation); (3) be detectable using remote sensing or other spatial proxies; (4) be interpretable to both experts and end users (e.g., conservation planners and policymakers).

Time series that account for the natural seasonal and interannual dynamism of the ecosystem should be prioritized over snapshot assessments (Chen et al., 2018; Slingsby et al., 2020). We also specifically consider foundational species, keystone species and ecosystem engineers, whose loss due to pressures may trigger cascading effects and ecosystem degradation (Bergstrom et al., 2015). Changes in ecosystem engineers may be detected with satellites, such as the transition from a closed-canopy vegetation to remnant trees in a matrix dominated by ephemerals in South Africa's Albany Thicket vegetation (Lechmere-Oertel et al., 2005; Lechmere-Oertel et al., 2005). Indicators should respond to the key pressures in an ecosystem, e.g., reduced productivity due to overgrazing (Vermeulen et al., 2021), or woody plant cover expansion due to bush encroachment (Skowno et al., 2017). Different indicators should be assessed individually and not as a composite index, as suggested by the RLE (IUCN, 2024). For national reporting and only, if necessary, these indicators may be weighted and aggregated into an overall condition score at the end of the workflow.

Step 5: Select appropriate remote sensing metrics and identify data sources

Appropriate remote sensing metrics that can either detect or approximate the selected indicators of ecosystem condition must be identified (Appendix S2: Table S2). Metric selection should be guided by the ecosystem-specific ecological mechanisms of change and the pressures identified in Step 2. For example, woody expansion in a historically non-woody ecosystem may be detected using greenness or fractional woody cover (Venter et al., 2018), while structural shifts may require complementary sensor data such as Synthetic Aperture Radar (SAR; Lopes et al., 2020) or canopy height products.

Metric choice should consider spatial resolution (ability to capture the scale of ecological change), temporal resolution (single-season *vs.* multi-year dynamics), sensor type (optical, LiDAR, SAR) and ecological suitability (e.g. Soil-Adjusted Vegetation Index for arid systems). We recommend a transparent indicator–metric matrix based on literature and expert input (e.g., Appendix S2: Table S2). Where feasible, RS approaches should be designed to be sensor-agnostic and transferable across multiple satellite platforms (e.g., Landsat and Sentinel-2), so that time series remain robust to sensor degradation, decommissioning, or access constraints (e.g., changes affecting Aqua/MODIS; Pettorelli et al., 2016). Many studies are available to guide the selection of remote sensing metrics to detect indicators of ecological condition (Bradley et al., 2007; Ezaidi et al., 2022; Jakobsson et al., 2021; Kairis et al., 2014).

Because this workflow targets degradation (not only habitat loss), analyses must explicitly separate ecosystem condition changes from natural vegetation dynamics, including intra-annual and inter-annual phenology and climate-driven variability. Recent advances in using phenology metrics to assess vegetation change show promising results (Dronova & Taddeo, 2022; Gong et al., 2024). The greening and browning cycles in intact vegetation often differ from vegetation in different stages of degradation (Wessels et al., 2007). We therefore recommend using methods that may standardize seasonality and climate effects, such as phenology metrics, e.g., season length (Dronova & Taddeo, 2022), matched-season comparisons (Thompson et al., 2009) and multi-year baselines. Field data remain essential to define reference conditions, calibrate model outputs, and verify that selected metrics reflect ecological reality.

Two analytical pathways are commonly effective and reproducible: (i) deviation-from-reference approaches, which quantify departures from intact spectral, geospatial or phenological signatures, either observed (Harwood et al., 2016) or modelled (Slingsby et al., 2020), and (ii) spatial modelling approaches (e.g., random forests) that use machine learning to analyze the relationships between RS predictors, environmental covariates, and training data representing ecosystem condition or land degradation (Bell et al., 2023; Sengani et al., 2025; Symeonakis & Higginbottom, 2014). Both approaches can be implemented at pixel level using freely available Earth observation data (e.g., Landsat, Sentinel-2, MODIS), then aggregated to reporting units (ecosystem types, protected areas, or accounts) as needed. Recent advances in satellite embeddings (e.g. AlphaEarth's embeddings dataset) are useful for spatial modelling as they compress multi-sensor and multitemporal information (Brown et al., 2025), reducing satellite pre-processing steps. Combined with expert knowledge of ecosystems that may produce high quality condition training data, supervised classification of ecosystem condition may be possible using spatial modelling. However, embeddings have no inherent ecological meaning as predictors, so indicator-based design, reference states, and field validation are still needed to interpret results and link outputs back to ecologically meaningful condition indicators (Appendix S2: Table S2).

Step 6: Select thresholds and map ecosystem condition

The workflow is intended to provide a structured pathway that quantifies both the severity of degradation and its extent across the ecosystem. Representing ecological condition as continuous variables provides a more realistic proxy for natural processes, which are typically governed by gradual, continuous variation rather than by discrete categories (van der Merwe et al., 2023). Where thresholds are required for assessments, continuous metrics can be calibrated to relative severity, expressed as proportional change from a defined reference state (low severity) toward a defined collapsed state (high severity), and then summarized by the proportion of the ecosystem distribution exceeding specified severity thresholds (IUCN 2024). For example, where high woody cover is detrimental to an ecosystem, it can be mapped as a continuous fractional cover surface (Venter et al., 2018), with relative severity defined by increasing departure from reference woody cover (e.g., near-zero in an intact grassland). Select ecologically justified breakpoints (e.g., cover levels associated with suppressed herbaceous biomass or altered fire behavior), ideally informed by published literature and expert knowledge and supported by state-and-transition models (Bestelmeyer et al., 2011; Briske et al., 2005), rather than based on arbitrary statistical cut-offs. We recommend documenting any threshold choices with written definitions, reference photographs and satellite-image examples, and clear statements of the intended use (e.g., risk reporting *vs.* management action), to support transparency and expert consensus. Ecosystem condition mapping may be implemented using deviation-from-reference approaches, spatial predictive modelling, or other calibrated scoring methods (Bell et al., 2023; Darko et al., 2024; Harwood et al., 2016) depending on choices in step 5. Regardless of method, outputs should be validated against field-based condition estimates, with uncertainty explicitly quantified and mapped (Lark et al., 2022; Singh et al., 2024). Iterative rounds of expert review are recommended to refine maps and build consensus, helping ensure that outputs align with ecological understanding and intended application. The resulting continuous layers can then be aggregated to reporting units such as ecosystem types, provinces or protected areas, used for trend analysis, and translated into categories where required for assessment, management prioritization or policy reporting.

Case study in Arid Thicket

The Albany Thicket Biome is a structurally complex and compositionally diverse vegetation that occupies a transitional zone between South Africa's arid interior and its more mesic coastal regions, varying along key environmental gradients from west to east. Arid Thicket vegetation dominates the interior valleys and escarpment foothills of the biome, where annual rainfall is low (200-350 mm) and erratic (full description in Appendix S1). Intact Arid Thicket is characterized by evergreen vegetation comprising a dense, mixed and low canopy of diverse succulent species, including dominant species like *Portulacaria afra* and various *Euphorbia* and *Crassula* species, and a woody component comprising a handful of tree species (*e.g. Pappea capensis, Euclea undulata* and *Schotia afra*), with grasses being generally rare (Vlok et al., 2003). In Step 1, the assessment was set up by identifying three experts and delineating the ecosystem types that fall within Arid Thicket using the NVM 2024. Unlike Grasslands and Savannas, intact Albany Thicket vegetation is fire-intolerant and fire-resistant, and thus the more stable and evergreen nature of the intact vegetation makes it feasible to monitor with remote sensing (Carvalho et al., 2022).

Because the key pressures that lead to habitat loss have already been measured (Fig. 2; Skowno et al., 2021), in Step 2, we focused on livestock production and ranching as the key pressure due to historical and continued unsustainable browsing in Arid Thicket, especially by goats, with sheep and extralimital wildlife also contributing to degradation (Lechmere-Oertel et al., 2005a; Mills et al., 2005). Chronic herbivory leads to canopy break-up and the loss of plant species that cannot escape the browse-trap imposed by sustained browsing pressure, as well as an increase in bare soil, which triggers soil erosional cycles (Mills et al., 2015; Mills & Cowling, 2006; Rutherford et al., 2014). While it may vary locally, chronic herbivory generally initiates a vegetation state shift from closed-canopy, near-impenetrable vegetation to open shrublands or in some areas to pseudo-savanna-like systems, often dominated by ephemeral alien forbs or annual grasses (Lechmere-Oertel et al., 2005b). In Step 3, intact reference conditions were described (Appendix S1) based on a consensus view of intact Arid Thicket vegetation (Mills et al., 2005; Vlok and Euston-Brown, 2002) and operationalized using 230 intact reference sites identified by Thicket ecologists within Arid Thicket ecosystem types across the east-west environmental gradient.

In Step 4, we focused on the loss of vegetation cover associated with compositional change consistent with browsing-driven opening up of the vegetation and the exposure of bare ground (Lechmere-Oertel et al., 2008) as the indicators of ecosystem condition. In step 5 and 6, we first masked transformed land cover classes using the SANLC 2022 data, with only "natural" and "semi-natural" classes remaining. Spectral and geospatial similarity was used to approximate ecosystem condition (Darko et al., 2024; Muise et al., 2025). Deviation from intact Arid Thicket was calculated using the AlphaEarth Foundations model's annual embeddings dataset available in the Google Earth Engine data catalog (Brown et al., 2025). The embeddings provide a ready-to-use annual 64-dimensional representation of multi-spectral and multi-temporal information derived from various Earth observation sources (e.g., Landsat and Sentinel-2 optical data, SAR, and DEM), designed to capture vegetation dynamics, land-cover patterns, and environmental gradients at 10 m spatial resolution (Brown et al., 2025). Each 10 m pixel in Arid Thicket was represented by a 64-dimensional annual embedding vector in 2022, a drought year in this biome. An intact reference centroid was derived as the mean embeddings vector across the intact reference sites and deviation from intact vegetation was quantified as the cosine distance in this multi-dimensional feature space (1 - cosine similarity), measuring how far each pixel's embeddings vector diverges in direction from the intact centroid. This is analogous to the use of Euclidean distance in multivariate ecological space (Harwood et al., 2016), but with cosine distance capturing differences in feature configuration rather than magnitude. Pixels with low cosine distance are most similar to intact sites, whereas higher cosine distance indicates progressively greater deviation (Darko et al., 2024), often consistent with higher bare soil cover (Fig. 3). Uncertainty was quantified using 100 bootstrap resamplings of the intact reference dataset, where the intact embeddings centroid and cosine distance surface were recomputed with each resample (Fig. 3). Because embeddings include environmental data, such as climate data, it is important to select reference sites across the range of the environmental gradients of Arid Thicket to avoid misinterpretation of natural gradients, such as the east-west aridity gradient, as degradation.

Spatial uncertainty was then summarised as the per-pixel standard deviation of cosine distance across bootstrap resamples, showing where deviation estimates are most sensitive to the selection of intact reference sites (Fig. S2). The resulting ecosystem condition map matched known Arid Thicket degradation patterns (e.g., along piospheres and fence-line contrasts; Fig. 4). Cosine distance across Arid Thicket ranged from 0.01 to 0.87 (mean = 0.37, median = 0.37, SD = 0.13), indicating substantial spatial variation in departure from the intact reference condition. Pixels with cosine distance exceeding the 95th percentile (p95 = 0.20) of intact reference sites were interpreted as departing from the expected baseline distribution of the intact sites and were considered likely degraded. Of the 793 803.04 ha assessed, 87% of Arid Thicket was considered degraded (703 315.73 ha).

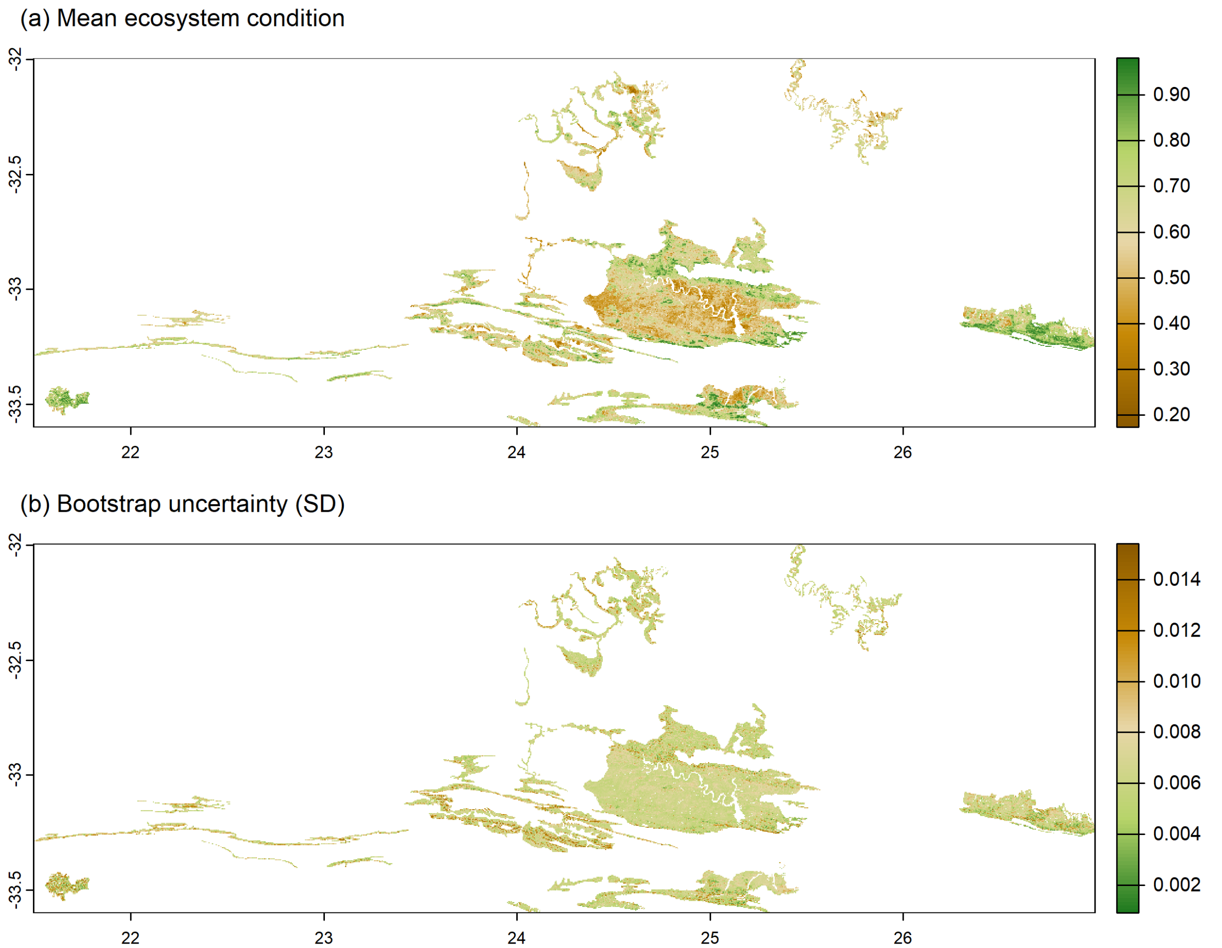

Figure 3. Embeddings-based ecosystem condition estimates for Arid Thicket in South Africa derived from the deviation from an intact reference centroid. (a) Mean ecosystem condition, scaled from low condition (brown) to high condition (green), where higher values indicate greater similarity to the intact reference state as measured by cosine distance in multi-dimensional feature space. (b) Bootstrap uncertainty, expressed as the pixel-wise standard deviation (SD) in condition estimates across bootstrap replicates generated by resampling the intact reference site embeddings. Low SD values indicate spatially stable condition estimates, whereas higher SD values indicate areas where condition estimates were more sensitive to variation in the reference sample, although SD was generally low.

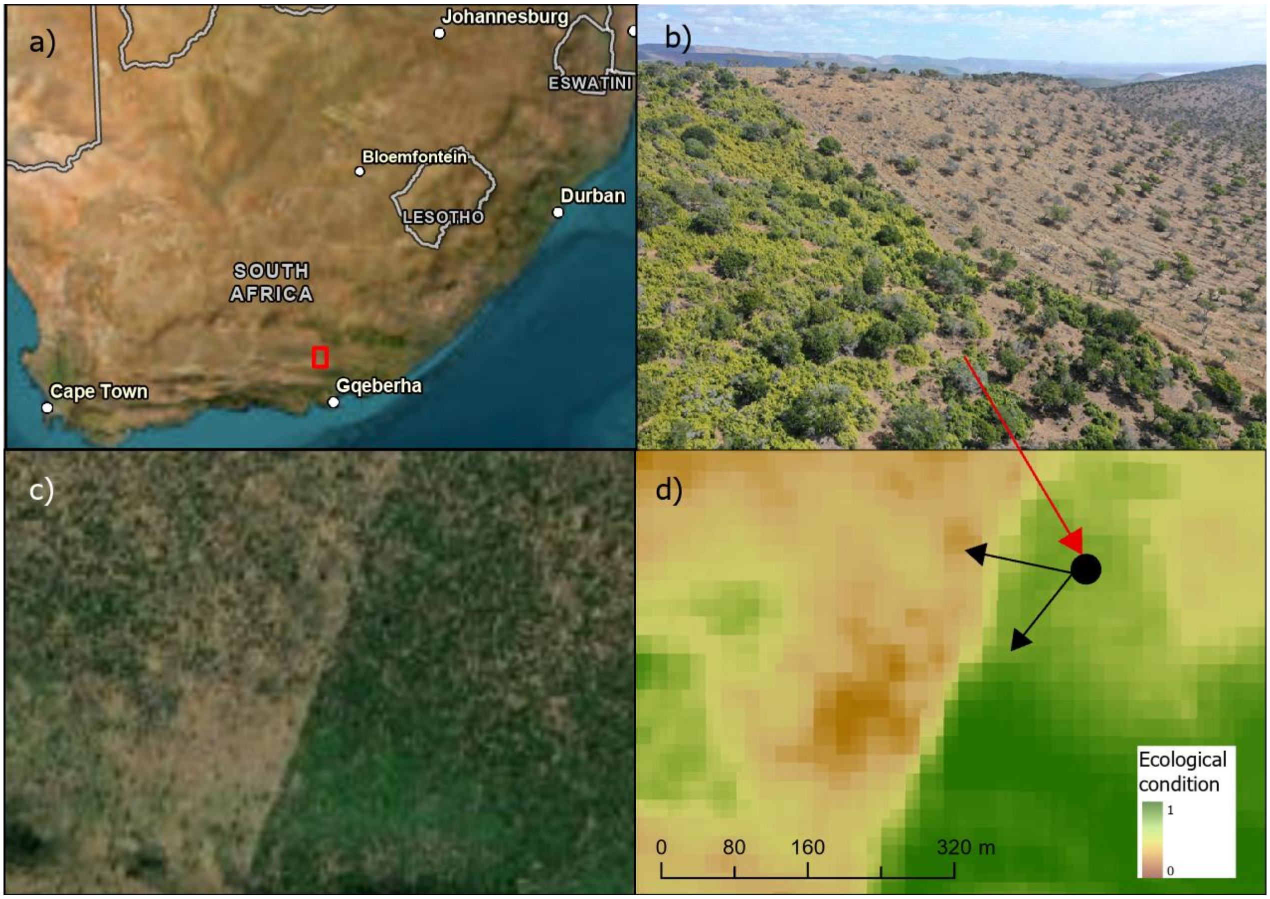

Figure 4. Ecological condition (inverse of cosine distance) of Arid Thicket vegetation demonstrated by a fence-line contrast where vegetation has been heavily browsed. The map in a) shows the location of the proof-of-concept site in South Africa, b) shows a drone photograph of the site, with c) showing satellite imagery (ESRI basemap) and d) the ecosystem condition for the same area calculated as the deviation from known intact sites, with greener colors indicating more closed canopy intact vegetation states (i.e. inverted cosine distance scaled to 0-1) and browner colors indicating more degraded open vegetation states. The approximate location and direction of the drone is indicated in d). Within 100 m of the fence-line, the relatively intact side had a mean cosine distance of 0.05 ± 0.04 (SD), whereas the heavily browsed side had 0.26 ± 0.03 (SD), indicating a consistent increase in departure from the intact reference condition under chronic browsing pressure. Notice the pseudo-savanna state of Arid Thicket on degraded side of the fence in b) where high browsing pressure has removed succulent and palatable species and altered the vegetation structure to an open system with remnant trees and high bare soil cover during dry periods.

Discussion

Assessing ecosystem condition requires integrating information and data on ecosystem composition, structure and function, drawing on a broad body of ecological knowledge across multiple disciplines. This breadth of information can be both a strength and a challenge for those attempting to design or apply ecosystem condition assessments in practice (Keith et al., 2020b; Williams & Pettorelli, 2025). The aim of this paper was to provide clear and actionable guidance for researchers, practitioners, and land managers undertaking ecosystem condition assessments in resource-limited, complex and data-variable landscapes. A key strength of this workflow is its flexibility and context-specificity, by using locally defined ecosystem types and knowledge. Unlike conventional land-cover change methods that are well suited to quantify habitat loss, the workflow suggests approaches that detect often subtle, gradual degradation within natural remnants. The six-step process is aligned with both SEEA EA (Edens et al., 2022) and the RLE (IUCN, 2024), bridging global standards while supporting national biodiversity reporting, restoration planning, and potentially emerging biodiversity markets (Xiao et al., 2024). In doing so, it offers an operational framework for assessing ecosystem condition along a continuum of change.

Remote sensing as a scalable operationalization tool

The Arid Thicket case study provided a practical test of the proposed workflow. It demonstrated that remote sensing can be effectively operationalized to map ecosystem condition as a continuous measure of degradation severity and extent. The use of embeddings was particularly valuable, as it integrates multi-sensor, environmental and temporal information, enabling subtle differences in ecosystem structure and dynamics to be detected beyond what single indices or bands may capture. The resulting ecosystem condition map for Arid Thicket provided finer scale mapping than previous efforts (Lloyd et al., 2002), capturing fine scale browsing-induced canopy opening along piospheres. Overall, the effectiveness of remote sensing for condition assessment is contingent on ecologically meaningful indicator selection (Rowland et al., 2018), guided by the response to key pressures and the ecological experts to select robust, well-distributed reference data (Vermeulen et al., 2025). Integrating expert knowledge with RS data is therefore not only a supplement to RS, but a prerequisite for ecosystem condition assessments and mapping. Expert interpretation of high-resolution imagery, field observations from study sites and ecological research can all be used to define reference conditions and construct training data sets. Importantly, this approach enables ecological expertise to be translated into scalable spatial products that support conservation planning and monitoring at regional and national scales (Vermeulen et al., 2025).

Challenges in defining reference conditions

One of the most important challenges in ecosystem condition mapping is defining appropriate reference conditions and selecting reference sites (Durbecq et al., 2020; Jakobsson et al., 2020). In Arid Thicket, defining reference conditions was facilitated by the presence of strong contrasts between intact and degraded states, particularly along fence-line boundaries and piospheres. Without stratification of reference sites, natural east-west gradients (200-350 mm mean annual precipitation) would have been conflated with degradation signals. Despite this, areas with limited reference data showed increased uncertainty, reinforcing the importance of adequately sampling reference conditions across the full environmental space of the ecosystem. In more dynamic or disturbance-driven ecosystems, such as Grasslands (Jacquin et al., 2016) or Savannas (Abdi et al., 2022), where vegetation structure and productivity respond strongly to interannual climate variability, or disturbance events such as fire, defining reference conditions is more challenging (Jakobsson et al., 2020). In such cases, multi-year time series can help address this challenge in the analytical steps by characterizing the typical range of ecosystem behavior rather than relying on individual observations (Arévalo et al., 2020), and/or characterizing the response of ecosystems to changes in environmental drivers (Slingsby et al., 2020). Metrics derived from temporal patterns, such as phenological characteristics (Chen et al., 2018) or long-term productivity trends (Graw et al., 2017; Lomax et al., 2025), may therefore provide more robust indicators of ecosystem condition in Steps 4 and 5, in such systems where seasonal or climatic variability is high.

Uncertainty and the need for validation

Although all RS-based condition assessments have inherent uncertainty, from atmospheric noise, model assumptions, threshold selection or sensor limitations, techniques such as time-series smoothing, ensemble modelling (Belgiu & Drăguţ, 2016) and uncertainty quantification (Singh et al., 2024) can reduce or account for such error. The bootstrap uncertainty analysis showed that condition estimates were generally robust, with low variability across most of the study area, reflecting sensitivity of condition estimates to the selection and representativeness of intact reference sites, providing a measure of how consistently condition can be estimated given variation in the reference baseline. In more dynamic ecosystems, uncertainty may be substantially higher and more difficult to interpret. This highlights the need for explicit uncertainty quantification and validation using independent field observations wherever possible. The fence-line contrast in Arid Thicket (Fig. 4) provided field-validation with a 0.21 mean ecosystem condition difference between the intact and degraded sites. Long-term monitoring applications will require periodic updating of training datasets (Woodcock et al., 2020), as ecosystem states change over time due to land use, disturbance and ecological succession. Developing efficient approaches for maintaining and updating these datasets (Fonseca et al., 2021) remains a key research priority.

Analytical pathways for condition mapping

The case study demonstrated that a reference-based deviation approach is an effective pathway for mapping ecosystem condition as the degree of spectral or structural similarity between a given pixel and known intact reference sites (Harwood et al., 2016; Jakobsson et al., 2021) and shows promise for evergreen or relatively stable ecosystems. Notably, the approach performed well even with sparse, intact-only reference data, producing condition estimates that aligned with observed structural degradation patterns such as browsing-induced canopy loss (Lechmere-Oertel et al., 2005). However, this reliance on intact-only reference data may lead to overestimation of condition in some areas and may not fully capture intermediate degradation states in other biomes. Despite this limitation, the deviation-based approach provides an intuitive and transparent means of quantifying ecosystem integrity as distance from a reference condition (Harwood et al., 2016), particularly in ecosystems where degradation pathways are relatively consistent and structural signals are detectable.

In more dynamic ecosystems, or those influenced by multiple interacting pressures, temporal variability or alternative stable states, complex degradation pathways can obscure the relationship between similarity to reference conditions and ecological condition. In such contexts, spatial predictive modelling approaches (Hengl et al., 2018) may be more appropriate. Observed indicators of ecosystem condition states from field observations or expert interpretation may be used to train statistical or machine learning models that relate estimates of ecosystem condition to spatial predictors (Yan et al., 2022). These predictors may include remotely sensed metrics such as vegetation productivity or phenology, together with environmental covariates such as soils, topography, climate, land-cover variables or embeddings, which include many of these (see e.g. Brown et al. 2025). Machine learning algorithms, such as Random Forests or Convolutional Neural Networks, are particularly well suited to this task because they can capture complex, non-linear relationships and can integrate multiple types of spatial data (Breiman, 2001; Kattenborn et al., 2021). Once trained, these models can extrapolate ecological condition across large areas, allowing condition to be mapped even where direct observations are sparse.

Conclusion

This study demonstrates a practical and scalable approach for mapping ecosystem condition for any biome by integrating local expert knowledge and remote sensing to capture subtle gradients of degradation. The workflow provides a practical pathway for countries to contribute comparable condition data to global biodiversity reporting frameworks. The next steps are to test the workflow across more dynamic biomes, where reference conditions are less stable and degradation pathways are more variable, and to compare the performance of reference-based deviation and predictive modelling approaches. Further work is also needed to improve the selection and updating of reference and training data and to strengthen field-based validation.

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Author contributions

SVDM, ALS, VV, CS, MTH, GRM, JAS, JS, AJP conceived the ideas and designed methodology; SVDM, ALS and AJP collected and collated the data for the case study; SVDM analyzed the data and led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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Appendix S1: Supplementary information to manuscript **“Ecosystem condition assessments: A context-specific workflow to integrate local expert knowledge and remote sensing”**

Stephni van der Merwe, Vernon Visser, Colleen Seymour, M. Timm Hoffman, Glenn R. Moncrieff, Jasper A. Slingsby, Janine Steytler, Alastair J. Potts, and Andrew L. Skowno

Appendix S1

IUCN T1.2.1: Arid Thicket

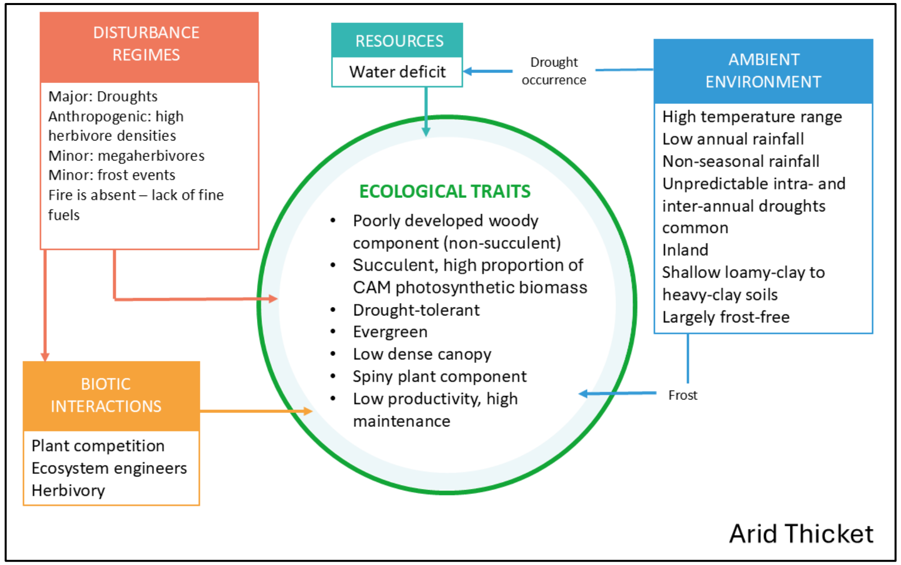
Biome: Albany Thicket, South Africa

KEY ECOLOGICAL TRAITS: Arid Thicket vegetation is functionally specialised to persist under severe abiotic stress and intermittent disturbance. Arid Thicket is distinguished from other Thicket forms by a poorly developed woody component and a prominent succulent layer, with communities being either dominated by *Portulacaria afra* (e.g. Spekboomveld) or by other succulents (e.g., *Euphorbia coerulescens* or *Euphorbia ledienii*). The canopy is low and dense (typically less than 2 m) and has less vertical stratification than Valley or Mesic Thicket. Grasses are rare. The Arid Thicket plant communities exhibit a high prevalence of spinescence. Species also show a weak frost tolerance and high drought tolerance, with widespread use of CAM photosynthesis and other water-conservation strategies. This ecosystem group is not adapted to tolerate fire, which is exceptionally rare due to the paucity of fine fuels (e.g. grasses); instead, it retains moisture—more than expected for an arid system—and efficiently recycles nutrients through litter decomposition and high root-to-shoot ratios. Growth rates are notably slow, limiting natural recovery from degradation.

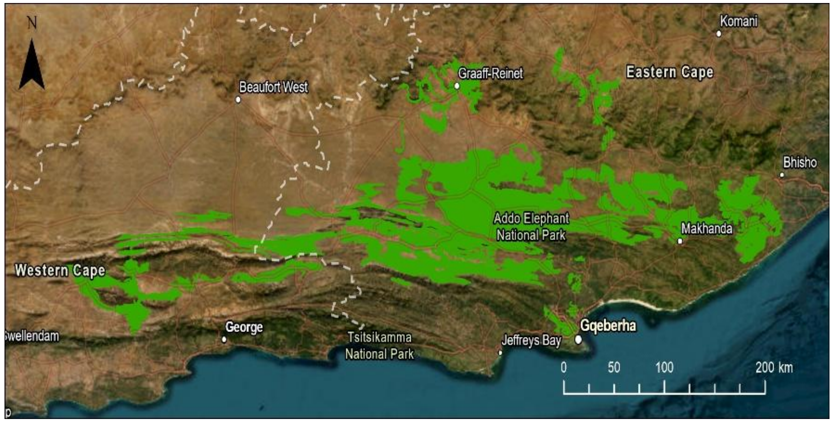
KEY ECOLOGICAL DRIVERS: Arid Thicket has strong environmental filters with long-term selective pressure. Water deficit is the principal abiotic constraint, due to low and variable annual rainfall (200-350 mm), high temperature range, and seasonal drought, primarily in the interior valleys of the Eastern Cape. These climatic constraints, coupled with shallow loamy-clay to heavy-clay soils, limit plant productivity and regeneration potential. More regular frost occurs in the escarpment zone, unlike other ecosystem groups in the biome. Arid Thicket has a low fine fuel load (e.g. lacks grasses), making it largely fire-excluding under intact and degraded conditions.

Key biotic interactions include plant competition for scarce water, especially among shallow-rooted succulents. Ecosystem engineers like *P. afra* and *Euphorbia* spp. play foundational roles in structuring microclimates and soil dynamics.

KEY PRESSURES: Historic clearing, increased climate variability and unsustainable grazing regimes, particularly by domestic goats and sheep or wild game, introduces chronic pressure that exceeds the regenerative capacity of the ecosystems, leading to canopy collapse, soil exposure, and replacement by ephemeral herbs and karroid perennial shrubs. These processes create feedback loops that reduce restoration potential without active intervention.



DISTRIBUTION: Patchy distribution on the valleys and slopes of Sundays, Fish, and Great Kei River catchments, along the foot slopes of the Great Escarpment and steep topography around Graaff-Reinet and Aberdeen. It is often found on shallow, loamy-clayey to clay soils in sandstone, or quartzite substrates, but is not substrate-specific. Sundays Spekboomveld and Sundays Noorsveld are representative of this ecosystem group.



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Appendix S2: Supplementary information to manuscript **"Ecosystem condition assessments: A context-specific workflow to integrate local expert knowledge and remote sensing"**

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Tabel S1. List of pressures in each biome in South Africa following the IUCN Threat Classification Scheme Level 2 based on expert opinion. Pressures are scored from 0-5 relative to the severity and extent of each pressure within a biome. Definitions for each pressure can be found in the supporting documentation of the IUCN Threat Classification Scheme.

Level 1	Level 2	IUCN code	Albany Thicket	Desert	Forest	Fynbos	Grassland	IOCB	Nama Karoo	Savanna	Succulent Karoo
Residential & commercial development	Housing & urban areas	1.1	2	1	2	3	3	4	1	3	1
Residential & commercial development	Commercial & industrial areas	1.2	2	1	1	3	3	3	1	2	1
Residential & commercial development	Tourism & recreation areas	1.3	1	1	1	1	1	1	1	1	1
Agriculture & aquaculture	Annual & perennial non-timber crops	2.1	3	1	2	5	5	5	1	5	1
Agriculture & aquaculture	Wood & pulp plantations	2.2	1	0	5	3	5	4	1	3	1
Agriculture & aquaculture	Livestock farming & ranching	2.3	5	4	1	2	3	3	4	3	4
Agriculture & aquaculture	Marine & freshwater aquaculture	2.4	na	na	na	na	na	na	na	na	na
Energy production & mining	Oil & gas drilling	3.1	1	2	1	1	2	1	2	1	2
Energy production & mining	Mining & quarrying	3.2	1	4	1	2	3	1	1	3	3
Energy production & mining	Renewable energy	3.3	1	2	1	1	2	1	2	1	2
Transportation & service corridors	Roads & railroads	4.1	1	2	1	1	1	1	2	1	1

Level 1	Level 2	IUCN code	Albany Thicket	Desert	Forest	Fynbos	Grassland	IOCB	Nama Karoo	Savanna	Succulent Karoo
Transportation & service corridors	Utility & service lines	4.2	1	1	1	1	1	1	1	1	1
Transportation & service corridors	Shipping lanes	4.3	na	na	na	na	na	na	na	na	na
Transportation & service corridors	Flight paths	4.4	1	1	1	1	1	1	1	1	1
Biological resource use	Hunting & collecting terrestrial animals	5.1	2	2	2	2	2	2	2	2	2
Biological resource use	Gathering terrestrial plants	5.2	2	3	3	2	2	2	2	2	3
Biological resource use	Logging & wood harvesting	5.3	1	0	4	1	1	2	1	3	1
Biological resource use	Fishing & harvesting aquatic resources	5.4	na	na	na	na	na	na	na	na	na
Human intrusions & disturbance	Recreational activities	6.1	na	na	na	na	na	na	na	na	na
Human intrusions & disturbance	War, civil unrest & military exercises	6.2	na	na	na	na	na	na	na	na	na
Human intrusions & disturbance	Work & other activities	6.3	na	na	na	na	na	na	na	na	na
Natural system modifications	Fire & fire suppression	7.1	1	1	2	3	3	3	1	3	1
Natural system modifications	Dams & water management/use	7.2	2	1	1	1	1	2	1	1	1
Natural system modifications	Other ecosystem modifications	7.3	na	na	na	na	na	na	na	na	na
Invasive & other problematic species, genes & diseases	Invasive non-native/alien species/diseases	8.1	2	1	3	4	3	3	1	3	2
Invasive & other problematic species, genes & diseases	Problematic native species/diseases	8.2	1	1	1	1	3	3	2	3	1
Invasive & other problematic species, genes & diseases	Introduced genetic material	8.3	na	na	na	na	na	na	na	na	na

Level 1	Level 2	IUCN code	Albany Thicket	Desert	Forest	Fynbos	Grassland	IOCB	Nama Karoo	Savanna	Succulent Karoo
Invasive & other problematic species, genes & diseases	Problematic species/diseases of unknown origin	8.4	na	na	na	na	na	na	na	na	na
Invasive & other problematic species, genes & diseases	Viral/prion-induced diseases	8.5	na	na	na	na	na	na	na	na	na
Invasive & other problematic species, genes & diseases	Diseases of unknown cause	8.6	na	na	na	na	na	na	na	na	na
Pollution	Domestic & urban waste water	9.1	1	1	1	1	1	1	1	1	1
Pollution	Industrial & military effluents	9.2	1	1	1	1	1	1	1	1	1
Pollution	Agricultural & forestry effluents	9.3	1	1	1	2	2	2	1	1	1
Pollution	Garbage & solid waste	9.4	1	1	1	1	1	1	1	1	1
Pollution	Air-borne pollutants	9.5	2	1	1	1	2	1	1	2	1
Pollution	Excess energy	9.6	0	0	0	0	0	0	0	0	0
Geological events	Volcanoes	10.1	na	na	na	na	na	na	na	na	na
Geological events	Earthquakes/tsunamis	10.2	na	na	na	na	na	na	na	na	na
Geological events	Avalanches/landslides	10.3	na	na	na	na	na	na	na	na	na
Climate change & severe weather	Habitat shifting & alteration	11.1	1	3	1	1	1	1	2	1	2
Climate change & severe weather	Droughts	11.2	1	4	1	2	1	1	3	1	3
Climate change & severe weather	Temperature extremes	11.3	1	4	1	1	1	1	3	1	3
Climate change & severe weather	Storms & flooding	11.4	1	1	1	1	2	2	1	2	1
Climate change & severe weather	Other impacts	11.5	na	na	na	na	na	na	na	na	na
Other options	Other threat	12.1	na	na	na	na	na	na	na	na	na

Table S2. Examples of ecological indicators and remote sensing metrics for each of the key pressures in South Africa.

Note this is not an exhaustive list of indicators and metrics, but is intended to guide Steps 4 and 5 of this workflow.

The selection is dependent on the ecological context of the study system.

Pressure	**Ecological indicator**	**Remote sensing metric (proxy)**	**Notes**
Unsustainable herbivory	Reduced vegetation cover, altered species composition or productivity	Mean NDVI/EVI, NDVI minimum, bare ground index, productivity trend, proximity to water sources	Works well in arid/semi-arid systems; multi-year trends preferred
Bush encroachment	Woody cover increase	Woody cover fraction, NDVI amplitude reduction, SAR VH/VV ratio	Woody cover increase at the expense of open systems (e.g. grasslands). Requires multi-year comparison or baseline reference
Fire regime disruption	Changes in fire frequency or fire return interval	MODIS Burned Area (MCD64A1), Sentinel-2 fire scars, time-since-burn layers	Fire regime changes affect structure, fuel loads, and successional stages
Woody invasive alien species	Proliferation of invasive trees or shrubs	Changes in canopy height (LiDAR), persistent NDVI greenness, classification maps	Often needs species-specific detection
Herbaceous invasives	Dominance of fast-growing or early-greening species	NDVI phase shift, NDVI skewness, seasonal peak detection	Phenological anomalies can flag presence; hard to confirm without field data
Soil erosion	Loss of topsoil or vegetation exposing bare ground	Bare soil fraction, albedo increase, TWI change	Best used with terrain models
Climate change	Shifts in seasonal timing or interannual productivity	Phenology trend, NDVI anomaly, CHIRPS rainfall trends	Used as contextual driver; difficult to isolate as a condition indicator
Pollution	Decline in water or vegetation quality near emission sources	Proximity to pollution source, VIIRS nightlights, water turbidity (Sentinel-2)	Not directly observable; use as supporting pressure data
Groundwater abstraction	Vegetation stress due to declining water availability	NDVI decline, early senescence, GRACE anomaly trends	May need integration with hydrological or field data
Overharvesting	Reduction in dominant species or vegetation structure	NDVI decline, biomass reduction, canopy cover loss (LiDAR/SAR)	Requires knowledge of harvested species and use intensity