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

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Open Research Statement

All data and code used in this study will be made publicly available in a suitable open-access repository upon acceptance of the manuscript.

Keywords

degradation detection; ecosystem condition accounting; ecological condition; ecological indicators; ecosystem condition; ecosystem condition mapping; expert knowledge; Red List of Ecosystems; remote sensing

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 developed a reproducible six-step workflow for assessing ecosystem condition across South Africa's terrestrial ecosystem types, and demonstrated it in Arid Thicket. Rather than prescribing universal indicators or analytical methods, the workflow standardizes the decision process for identifying ecosystem experts and assessment units, identifying key pressures, defining natural reference states, selecting ecological indicators and appropriate remote sensing metrics, and mapping and validating ecosystem condition. Expert knowledge guides decisions throughout. Arid Thicket is a dense, evergreen, woody-succulent vegetation where the key pressure, chronic livestock browsing, removes palatable plants, opens the canopy and exposes bare soil. However, this well-documented degradation pathway is poorly captured by national land cover products and remains classified as “natural”. Experts confirmed the natural reference state description, identified browsing-related ecological responses and verified 425 natural reference sites. AlphaEarth satellite embeddings were used, which summarizes remotely sensed surface characteristics of each pixel as a numerical signature. We averaged the signatures of natural reference sites and calculated cosine distance, with larger values indicating greater multivariate distance from the reference signature. We evaluated the distance metric against 425 independent expert-labelled sites representing “intact”, “moderately browsed” and “severely browsed” vegetation. Among reference sites, cosine distance was unrelated to rainfall or temperature and across expert-labelled sites, distance increased with browsing intensity (Spearman’s $\rho = 0.634$, $p < 0.001$) and reproduced fence-line contrasts. Thresholds selected by maximizing quadratic weighted kappa classified 75.3% of the remaining natural extent as severely browsed. The case study demonstrates the potential of reference-based condition mapping where natural reference sites are identifiable, one pressure dominates the degradation pathway and the ecological response produces a detectable signal. In more disturbance-driven ecosystems, or those affected by multiple interacting pressures, the workflow accommodates pressure-specific indicators, time-series metrics and alternative analytical approaches. The workflow complements existing ecosystem condition approaches by providing an explicit, expert-guided process for translating ecosystem-specific knowledge into spatial condition assessments. Its outputs could support biodiversity reporting, ecosystem risk assessments, ecosystem accounting and restoration prioritzation.

Introduction

Ecosystem condition assessments have become an important tool in conservation and restoration planning, to determine the state, functioning and condition 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". Ecosystem condition is the degree to which the composition, structure and function of an ecosystem have been modified from a reference condition of "natural" (South African National Biodiversity Institute [SANBI], 2023). By identifying patterns of degradation or resilience, ecosystem condition assessments help 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 goals (Nicholson et al., 2021). The rapidly growing carbon and biodiversity credit markets (Wunder et al., 2025) and advances in corporate biodiversity reporting (Bedford et al., 2026), create additional urgency for context-specific, but reproducible and scalable, assessment approaches. Although ecosystem 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 and expert-guided workflow for assessing ecosystem 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 the 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 in a 6-tier hierarchical typology, where Level 5 represents bottom-up global ecosystem types which are "complexes of organisms and their associated physical environment within an area occupied by an ecosystem functional group" (Level 3), "sharing similar ecological processes but differing substantially in biotic composition" (Keith et al., 2022). Level 6 subglobal ecosystem types are "subunits or nested groups of subunits within a global ecosystem type, with more compositional resemblance to one another, than other global ecosystem types" (IUCN, 2024; Keith et al., 2022). These represent units of established national classifications. The RLE approach assesses biodiversity loss of ecosystems by quantifying the risk of ecosystem collapse, defined as the loss of an ecosystem's defining biotic or abiotic features to the extent that it can no longer sustain its characteristic native biota (IUCN, 2024), whereas the SEEA EA framework 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 two criteria are central to risk classification but are applied less often than extent-based criteria (Skowno & Monyeki, 2021). In the SEEA EA, ecosystem condition accounts record selected biophysical characteristics of ecosystems through time, typically relative to a natural reference state, 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). Both standards also explicitly recognize that ecosystem-specific expertise is needed to select and interpret ecosystem condition indicators and to address gaps in empirical evidence (IUCN, 2024),

Ecologists who have studied particular ecosystems over many years accumulate a wealth of knowledge that extends beyond what is captured by the published literature alone. Through repeated field observations, engagement with land managers and synthesis of the relevant literature, ecological experts develop a deep understanding of an ecosystem's defining characteristics, natural variability, historical changes and responses to different pressures (Clements et al., 2024). This ecosystem-specific knowledge is particularly valuable for distinguishing degradation from natural variation, identifying ecologically meaningful natural reference states and selecting indicators that may reflect changes in ecosystem composition, structure and function. When incorporated into ecosystem condition assessment workflows, accumulated expert knowledge and literature can therefore provide a defensible ecological foundation for ecosystem condition assessment, particularly where long-term empirical data are limited.

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 broad 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. A growing range of global and regional spatial products (e.g. Parente et al., 2024; Theobald et al., 2025) can provide information relevant to ecosystem condition, but they cannot determine which ecological changes are most meaningful within a particular ecosystem or how those changes should be interpreted. RS-derived variables are proxies of ecosystem condition, requiring careful interpretation by ecologists. Many ecological characteristics, such as species composition or soil health, remain challenging to assess 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). Expert knowledge anchors the choices of RS approaches and provides reference and training sites for RS techniques (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 natural reference states.

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). We define a pressure as a proximate external activity, process or flux acting directly on an ecosystem and capable of changing its biotic or abiotic state, resulting in changes in ecosystem condition (Czúcz et al., 2021; IUCN, 2024). 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 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. Harwood et al. 2016). 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 degradation 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. These two requirements are needed for RLE assessments and are 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 that can be measured with satellite data. The central challenge is therefore to connect available spatial data with an ecosystem-specific understanding of natural reference states, key pressures and degradation pathways.

In South Africa, a megadiverse country (Mittermeier et al., 1997), 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's RLE (Skowno & Monyeki, 2021) uses the tNational Vegetation Map (NVM; Mucina & Rutherford, 2006) as the historical extent of ecosystems, cross-tabulated with the 20 m resolution South African National Land Cover (SANLC) products (Department of Forestry, Fisheries and the Environment, 2024) to calculate the remaining extent of ecosystems at different time steps. The same land cover data are used to do ecosystem extent accounts (Statistics South Africa, 2021). Although land cover data may accurately assess habitat loss (assessed in Criteria A and B of the RLE), 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), it has not been possible for the 78% of the country still classified as "natural" (Skowno et al., 2021). However, South Africa has a strong legacy of ecological and spatial biodiversity research, supported by an extensive degradation literature (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) and biome-specific ecological experts whose accumulated knowledge can inform ecosystem condition assessments.

Several national and regional initiatives have translated ecosystem condition concepts into operational assessment systems. Norway's Index-Based Ecological Condition Assessment (IBECA) quantifies condition by scaling ecosystem-specific indicators relative to natural reference values and defined limits for good condition, before aggregating them into broader condition estimates (Jakobsson et al., 2021). Australia's Habitat Condition Assessment System (HCAS) uses a spatial modelling approach that compares remotely sensed characteristics observed at a location with those expected if that location were in a natural reference condition, while accounting for natural environmental variation (Harwood et al., 2016; Owers et al., 2026). These approaches demonstrate that ecosystem condition can be assessed systematically at broad spatial scales. However, these approaches do not yet make expert knowledge an explicit, iterative input and do not provide a procedure for tailoring the process to a specific ecosystem, that can be applied universally. A key remaining challenge lies in translating an ecosystem-specific local ecological understanding into a defensible spatial condition assessment while remaining method-flexible.

We therefore developed a six-step, expert-guided remote sensing workflow to support continuous ecosystem condition assessment across South African ecosystem types. Our objectives were to formalize the decision process, demonstrate its implementation in Arid Thicket, South Africa, and identify the conditions and limitations relevant to possible application in other ecosystems or countries. 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). .

Methods

Study area

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 south-eastern coastal regions (Vlok et al., 2003). Arid Thicket vegetation dominates the interior valleys and escarpment foothills of the biome, where annual rainfall is typically low (200-350 mm) and erratic (full description in Appendix S1). 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).

Arid Thicket was selected as a proof-of-concept because its main degradation pathway is well documented (Lloyd et al., 2002; Mills et al., 2015; Mills & Cowling, 2006; Rutherford et al., 2014) and produces changes in vegetation structure and cover that are visible in satellite imagery, even to the naked eye. Chronic browsing by domestic livestock, particularly goats, leads to a loss of palatable species, a decrease in canopy cover, increased bare ground exposure and soil erosion (Lechmere-Oertel et al., 2005a). While it may vary locally, chronic browsing generally initiates an

ecosystem condition shift from closed-canopy, near-impenetrable vegetation to open shrublands or to pseudo-savanna-like systems, often dominated by ephemeral alien forbs or annual grasses (Lechmere-Oertel et al., 2005b). Unlike strongly seasonal grassy ecosystems in South Africa, Arid Thicket retains a relatively stable evergreen canopy signal, and fire is not a natural disturbance regime here, reducing the likelihood that seasonal greening and senescence may be mistaken for degradation. Natural and heavily browsed vegetation frequently occur in close proximity across fence-lines and in piospheres around livestock concentration points, providing ecological contrast while limiting differences in climate, soils and topography (Lechmere-Oertel et al., 2008). Decades of accumulation of local expert knowledge and degradation research also provided a strong foundation to test whether an expert-guided RS approach can detect degradation that is not captured as land cover conversion (Kerley et al., 1995; Lechmere-Oertel et al., 2005b; Lloyd et al., 2002).

Workflow steps

Because open access RS data at the resolution required to detect species composition is still in its infancy (Cardoso et al., 2025), this workflow (Fig. 1) focuses on vegetation structure and function. It supports assessment of biotic disruption and environmental degradation within the remaining natural extent, including applications under RLE Criteria C and D (IUCN, 2024). Here we view ecosystem condition from an intrinsic, ecocentric perspective (H. Keith et al., 2020), along a gradient from "intact" to fully collapsed ecosystems, similar to the RLE (IUCN, 2024). We use "natural reference state" for the ecological benchmark describing expected composition, structure and function under minimal human modification (SANBI, 2023), and "intact" for sites or mapped pixels assigned to the highest condition class relative to that benchmark.

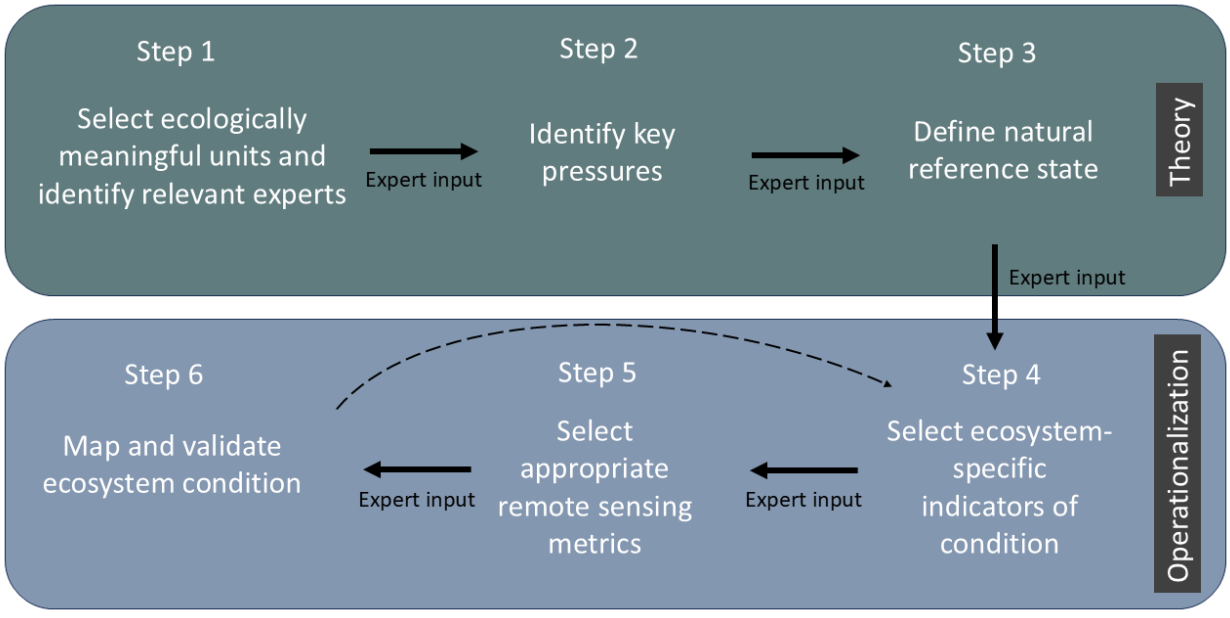


Figure 1. Six-step, expert-guided workflow for producing spatial ecosystem condition assessments from remote sensing data. The workflow begins with published evidence and ecological theory, while expert knowledge and elicitation inform decisions throughout all steps.

Step 1: Select ecologically meaningful assessment units and identify relevant experts

The first step is to conduct an extensive literature review and identify relevant local ecological experts to assist throughout the process and 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, have a publication record related to the ecosystems, extensive field experience and ideally some experience with RS. Experts must co-define the degradation pathways, natural reference states, and indicators of ecosystem condition, and supply or validate training data and condition maps so that the RS 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). An assessment unit is a mapped ecosystem type, or an ecologically justified group of ecosystem types, within which condition is evaluated against a shared natural reference state and pressure-response pathway. In South Africa, the NVM provides both a terrestrial ecosystem typology and a mapped representation of potential ecosystem extent (Mucina & Rutherford, 2006). 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 (D.A. 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). In countries 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.

Case study implementation: The assessment was set up by conducting a literature review in Arid Thicket and identifying three Arid Thicket experts (co-authors AJP, MP, ARP) with a publication record, RS experience, willingness to participate and ongoing field research in Arid Thicket with a combined 100 years of experience in the Albany Thicket biome. We selected the five ecosystem types that fall within Arid Thicket using the NVM 2024. Expert elicitation occurred via emails, online meetings and in-person at the Thicket Forum conferences of 2024, 2025 and 2026. Experts, as well as the broader community of Thicket ecologists present at these meetings, provided input. Decisions were reached through majority agreement between experts and all three validated the natural reference sites, provided independent browsing intensity observations and reviewed the final condition map in later stages.

Step 2: Identify key pressures

A central challenge in ecosystem condition assessments lies in identifying the key ecological characteristics and indicators that adequately reflect the fundamental processes underpinning

ecosystem condition and its change (Czucz et al., 2021). 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; providing the foundation for Step 3's description of natural reference state and Step 4's selection of fit-for-purpose indicators. The practical starting point is the systematic identification of relevant pressures. The IUCN Threats Classification Scheme (IUCN, 2022) 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 South African National Land Cover (SANLC) or other global land cover products already capture outright conversion by crop production, urban development, plantations and mining (Skowno et al., 2021; Fig. 2). The approach presented here often targets 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 pathways; the causal sequence linking a pressure to changes in ecosystem composition, structure or function and hence to declining ecosystem condition. 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

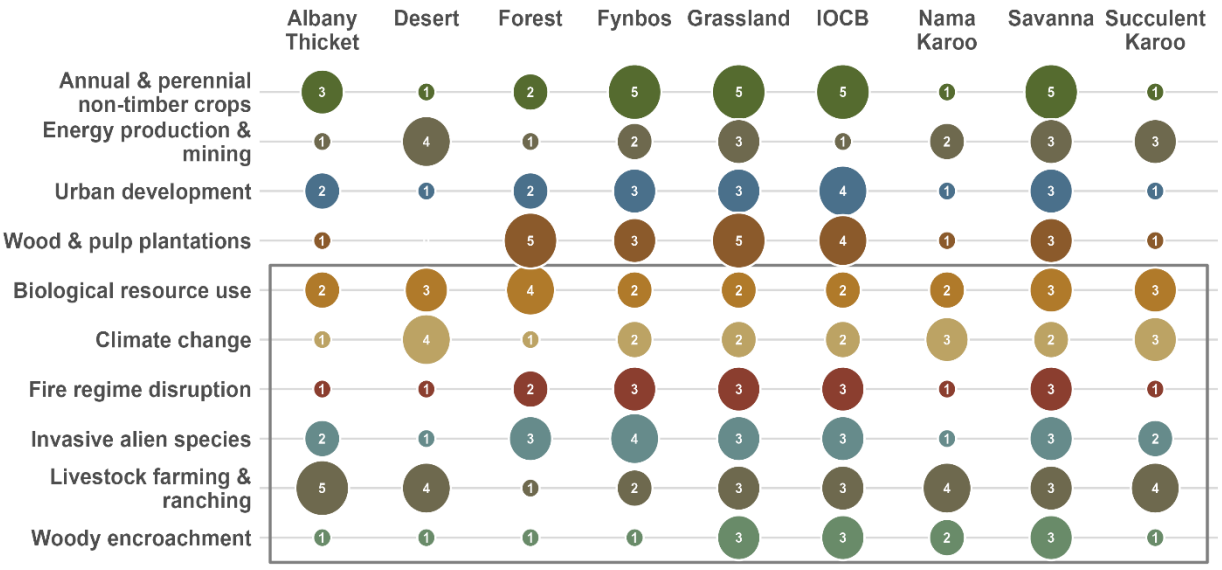


Figure 2. Key pressures per biome in South Africa, summarized from the full list of pressures in the IUCN Threats Classification Scheme (Appendix S2: Table S1), which includes both historical and contemporary pressures. The top rows represent pressures that can already be measured using national land 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, and zero indicates that 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.

being the most impacted biomes in South Africa (Fig. 2), this is a critical step for the indicator and metric selection steps.

Case study implementation: Livestock production and ranching is the key pressure in Arid Thicket due to historical unsustainable browsing by goats and sheep and continued chronic browsing associated with commercial mohair production and subsistence farming in rangelands (Lechmere-Oertel et al., 2005b; Mills et al., 2005). Experts confirmed this and agreed with the ranking of browsing as the dominant pressure. Arid Thicket degraded by chronic browsing is not currently detected in the SANLC data (currently used for RLE assessments in South Africa), with most of Arid Thicket being classified as "low shrubland" or "natural grassland". The pixels that fall within natural reference states of Arid Thicket are currently classified as "dense forest and woodland", "contiguous low forest & thicket" or "open woodland" in the SANLC.

Step 3: Define natural reference state

Without clear benchmarks, the assessment of ecosystem condition becomes somewhat arbitrary. The natural reference states provide a clear ecological baseline from which deviation can be measured (Gann et al., 2019), based on each pressure identified in Step 2. The RLE 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 state that reflects a sustainable long-term average (Czucz et al., 2021; Xiao et al., 2024). Our workflow directly incorporates this principle by requiring descriptions of natural reference states, and identification of example natural reference sites, developed with ecosystem experts. Once key pressures are known, the descriptions should state the natural range of variability to select indicators in Step 4 that may respond to the pressures.

The location of natural reference sites will be used in later stages of the workflow as training points. These natural reference sites should reflect the structure, composition, and function of a healthy ecosystem prior to significant anthropogenic disturbance from pressures (Durbecq et al., 2020; Edens et al., 2022; Gann et al., 2019). Many ecosystems in South Africa are dynamic and vary substantially with natural disturbance regimes (Bond et al. 2003) and their variations (e.g., post-fire recovery, rainfall seasonality). Therefore, to avoid conflating natural fluctuation with degradation, reference sites should be selected to capture the expected range of variability by sampling across natural environmental gradients, using multi-year time series and/or disturbance-sensitive indicators in the next steps (see e.g., Slingsby et al., 2020).

Case study implementation: The five ecosystem types within Arid Thicket have previously been described in detail (Dayaram et al., 2019; Hoare et al., 2006). While species composition differs between these ecosystem types, the structure and cover observable with RS is similar, as well as the the impacts of the key pressure, thus the general natural reference state for Arid Thicket as an ecosystem group, was described from the literature (Mills et al., 2005; Vlok & Euston-Brown, 2002; Appendix S1). The description was confirmed by the experts and operationalized using 425 natural reference points that matched the description across Arid Thicket, with points placed across the east-west environmental gradient to account for natural variation. The natural reference points were extracted from a dataset from one of the experts that utilized fence-line contrasts across Arid Thicket for the selection of sites. The experts also confirmed the natural

reference sites using high resolution Google satellite imagery Google Maps satellite imagery (Google LLC; accessed 21 September 2026; https://maps.google.com/).

Step 4: Select ecosystem-specific indicators of condition

The selection of indicators translates ecological understanding (how and why ecosystems change) into variables that can be measured, interpreted and validated (Rowland et al., 2018; 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). 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 RS 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 in disturbance-driven ecosystems (Chen et al., 2018; Slingsby et al., 2020). We also specifically suggest focusing on foundational species, keystone species and ecosystem engineers, whose loss due to pressures may trigger observable cascading effects and ecosystem degradation (Bergstrom et al., 2015). Indicators should also 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 woody encroachment (Skowno et al., 2017).

Case study implementation: The literature suggested (Lechmere-Oertel et al., 2008; Lechmere-Oertel, et al., 2005a), and experts confirmed, canopy loss and increasing bare soil exposure as the principal remotely observable outcomes of chronic browsing in Arid Thicket. The loss of ecosystem engineers, such as *P. afra*, as a result of chronic browsing, transitions the ecosystem from a closed-canopy vegetation to remnant trees in a matrix dominated by ephemerals (Lechmere-Oertel et al., 2005b), or bare soil in the dry season, currently erroneously detected as "natural grassland" in the SANLC.

Step 5: Select appropriate remote sensing metrics

Appropriate RS metrics that can either detect or approximate the indicators of ecosystem condition selected in Step 4 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 RS metrics to detect indicators of ecosystem condition (Bradley et al., 2007; Ezaidi et al., 2022; Jakobsson et al., 2021; Kairis et al., 2014).

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 natural reference 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.

Two analytical pathways are commonly effective and reproducible: (i) deviation-from-reference approaches, which quantify departures from a natural reference state's 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 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) may be useful for deviation-from reference approaches or 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 expert validation are still needed to interpret results and link outputs back to ecologically meaningful condition indicators.

Case study implementation: Because loss of canopy cover and bare soil exposure occur together, we tested the use of the AlphaEarth annual satellite embeddings dataset (Brown et al. 2025), suggested by experts, as a multivariate remote sensing metric of their combined surface expression. It is available in the Google Earth Engine data catalogue, and provides a global, analysis-ready 64-dimensional representation of annual surface conditions learned from multiple Earth-observation sources (optical (Sentinel-2, Landsat 8/9), radar (Sentinel-1, ALOS PALSAR-2), LiDAR (GEDI), topographic (Copernicus GLO-30) and climate (ERA5-Land) data), designed to capture vegetation dynamics, land cover patterns, and environmental gradients at 10 m spatial resolution (Brown et al., 2025) . With satellite embeddings being multivariate, and requiring no pre-processing, it is an attractive option in resource-constrained countries, especially in South Africa with 476 ecosystem types and little resources. The embeddings were not treated as ecological indicators themselves; rather, they provided a feature space in which departure from

the natural reference state could be quantified. The experts then judged whether the outputs made ecological sense in Step 6.

All remote sensing analyses and climate data extractions were conducted in Google Earth Engine (Gorelick et al., 2017), whereas statistical analyses were conducted in R Statistical Software (R Core Team, 2024). We excluded converted land cover classes ("Cultivated", "Built up", "Mines and Quarries" in the SANLC 2022 level 1) and water ("Waterbodies") from the analysis and calculated the mean embeddings vector ("centroid") of the 425 natural reference sites. For each remaining pixel, deviation was calculated as cosine distance from this centroid, where zero indicated alignment with the natural reference centroid and increasing values indicate greater multivariate departure, likely driven by chronic browsing in rangelands, as the most prevalent pressure. This deviation-from-reference method was tested because reliable natural reference observations were available from the experts. Because satellite embeddings may encode natural environmental gradients, four WorldClim 2 variables (BIO1, BIO12, BIO15 and BIO17; Fick & Hijmans, 2017) were extracted at each natural reference site and tested separately against cosine distance using linear regression (R Core Team, 2024).

Step 6: Map and validate ecosystem condition

Where categorical maps are required for ecosystem accounting, assessment or policy reporting, continuous condition metrics must be translated into ecologically interpretable classes. Categorization also facilitates validation because experts can rarely assign precise continuous condition values, such as scores from 0 to100, but can more reliably classify sites into a small number of predefined condition classes or ordinal condition scores. Thresholds therefore provide a link between continuous remotely sensed metrics and observable ecosystem condition states.

Thresholds should represent ecologically meaningful levels of degradation and be informed by published evidence, expert knowledge and, where relevant, state-and-transition models (Bestelmeyer et al., 2011; Briske et al., 2005), rather than statistical patterns alone. Where sufficient expert-labelled observations are available, candidate thresholds can also be evaluated by maximizing agreement between mapped and expert-assigned ordinal classes, for example using quadratic weighted kappa (Fleiss & Cohen, 1973). For RLE Criterion D applications, these classes may additionally be related to the proportional change from a defined natural reference state towards ecosystem collapse (IUCN, 2024) for each pressure. Outputs should subsequently be evaluated against field-based condition estimates or expert-defined categories, with uncertainty quantified (Lark et al., 2022; Singh et al., 2024). Iterative expert review can then refine the mapped classes and ensure that they remain consistent with ecological understanding and their intended reporting or management application.

Case study implementation: Uncertainty associated with natural reference-site selection was evaluated by generating 100 stratified bootstrap centroids from the natural reference sites. The resulting centroid vectors were applied to the annual satellite-embedding image, where cosine distance surfaces for each pixel in the study area were calculated for each bootstrap replicate. The mean distance and its pixelwise standard deviation were then calculated across replicates to identify areas where mapped departure was most sensitive to reference-site selection.

To evaluate whether cosine distance corresponded to observable browsing intensity, the three experts provided an additional set of 425 labelled point obeservations, independent of the points used to construct the natural reference centroid. Sites were classified by experts as “intact”, “moderately browsed” or “severely browsed” using criteria described in Steps 3 and 4. Cosine distance values were extracted at expert-labelled sites using the *terra* package (Hijmans et al., 2026). We tested whether cosine distance increased across the ordered browsing intensity classes using Spearman’s rank correlation (Spearman, 1904) and compared moderate and severe sites with intact sites using pairwise Wilcoxon rank-sum tests (Wilcoxon, 1945), with p-values adjusted using Holm’s procedure (Holm, 1979).

To translate the continuous cosine distance surface into the three browsing intensity classes, we evaluated all possible pairs of cut-points located midway between consecutive observed distance values. We selected the pair that maximized quadratic weighted kappa between the expert-labelled and distance-derived classes (Cohen, 1968; Fleiss & Cohen, 1973). This criterion accounts for the ordinal structure of the classes by penalizing disagreement between intact and severe sites more strongly than disagreement between adjacent classes (Cohen, 1968). The selected cut-points were applied, and the resulting map was visually reviewed by the three experts. Although a full RLE assessment or ecosystem condition account was beyond the scope of this study, we quantified the area and proportion of each class within the remaining natural extent of each ecosystem type to demonstrate the potential application of the data using the *sf* (Pebesma, 2018), and *exactextractr* packages (Baston, 2024). The mapped patterns were additionally visually evaluated against known fence-line contrasts between intact and severely browsed vegetation.

Results

The natural reference centroid was stable to reference site resampling, with bootstrap centroids showing only small departures from the full-sample centroid (Fig. 3). Bootstrap uncertainty increased for points farther from the centroid but remained small in absolute terms, indicating that the estimated natural reference state was relatively insensitive to the selection of natural reference sites. Cosine distance across Arid Thicket ranged from 0.01 to 0.83 (mean = 0.34, median = 0.37, SD = 0.12), indicating substantial spatial variation in departure from the natural reference state (Fig. 3).

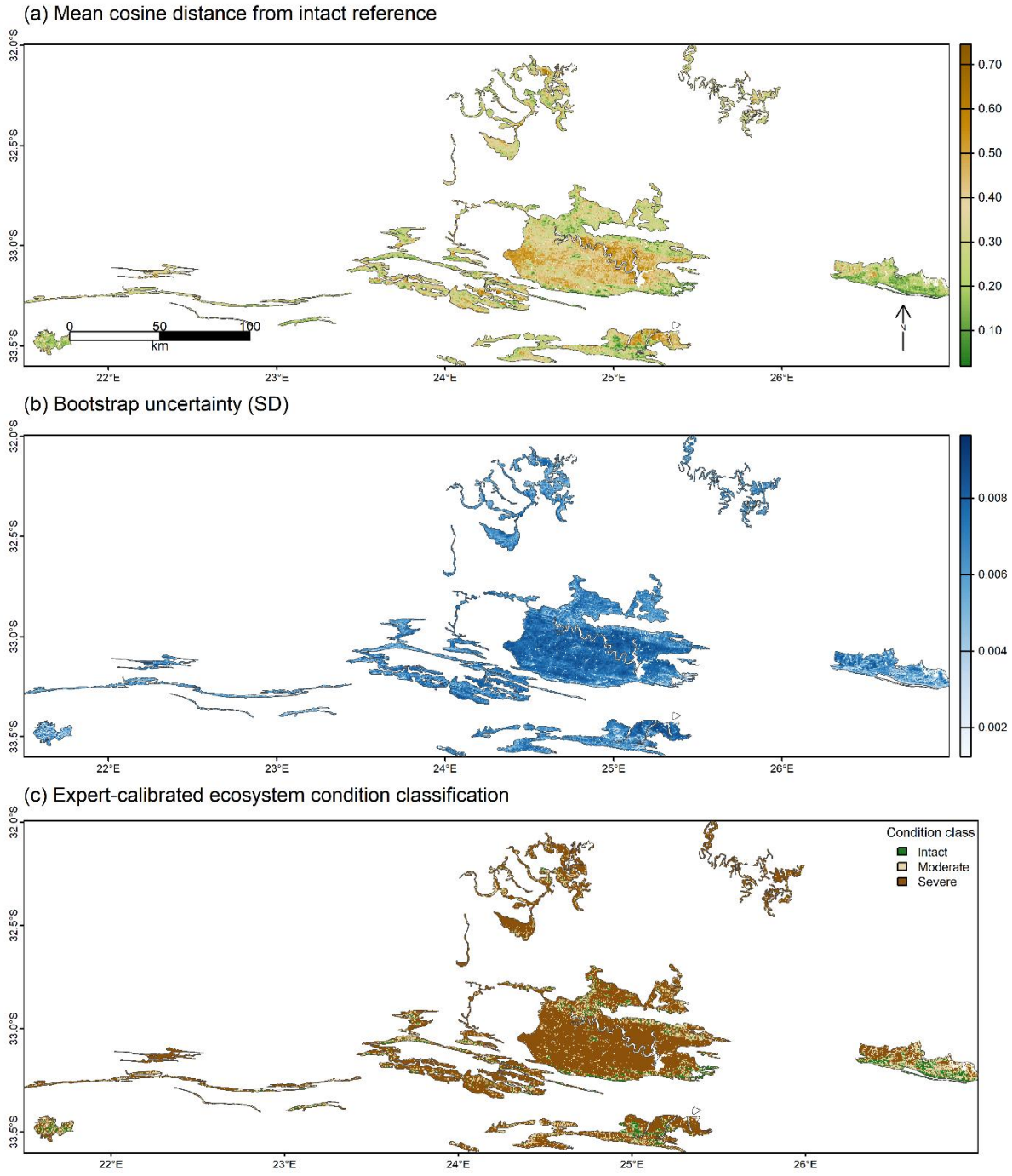


Figure 3. Embeddings-based ecosystem condition estimates for Arid Thicket in South Africa derived from the cosine distance from the natural reference centroid. (a) Mean cosine distance, where lower values indicate greater similarity to the natural reference state as measured by cosine distance in multi-dimensional feature space. (b) Bootstrap uncertainty, expressed as the pixel-wise standard deviation (SD) in condition estimates across bootstrap replicates generated by resampling the natural 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 natural reference sample, although SD was generally low. (c) Expert-calibrated ecosystem condition classification map.

Cosine distance among natural reference sites did not vary systematically with any climate variable and all regression-slope confidence intervals included zero ($F_{1,423}$ = 0.31–1.69, R^2 = 0.0007–0.0040, p = 0.194–0.578; Appendix S3: Figure S1). Cosine distance increased consistently (Fig. 3) across the browsing intensity classes (Spearman's ρ = 0.634, 95% bootstrap CI: 0.543–0.684, p = 4.31×10^{-49}), from a median distance of 0.103 for intact sites (n = 81) to 0.190 for moderately browed sites (n = 115) and 0.325 for severely browsed sites (n = 229). Moderate and severely browsed sites differed from intact sites (moderate: W = 6,340, rank-biserial correlation = 0.361, 95% CI: 0.196–0.517, Holm-adjusted p = 1.70×10^{-5}; severe: W = 16,352, rank-biserial correlation = 0.763, 95% CI: 0.645–0.868, Holm-adjusted p = 3.69×10^{-24}). Maximizing quadratic weighted kappa against the browsing intensity classes identified cosine distance thresholds of 0.139 between intact and moderately browsed condition and 0.256 between moderately and severely browsed condition, with a calibration agreement of weighted κ = 0.647 (95% bootstrap CI: 0.581–0.709); these thresholds were used to classify the continuous surface (Fig. 3). Across the 787,272 ha assessed, 75.3% was classified as severely browsed, 18.3% as moderately browsed and 6.40% as intact (Appendix S3: Table S1). Severely browsed condition was most extensive in Escarpment (82.1%) and Sundays Arid Thicket (78.8%), whereas Albany Arid Thicket was predominantly intact (75.1%) within the remaining natural extent (Appendix S3: Table S1). Fence-line contrasts between intact and severely browsed vegetation and visual interpretation by experts gave additional validation that the deviation-from-reference approach captured known degradation gradients (Fig. 4).

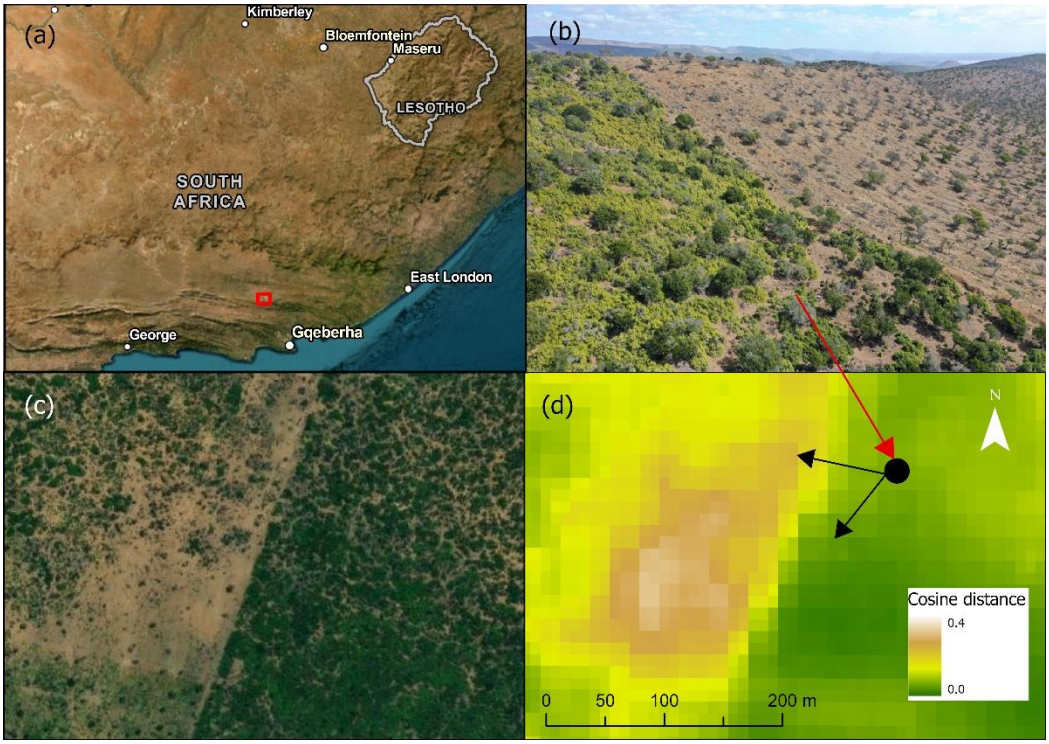


Figure 4. Ecosystem condition of Arid Thicket vegetation demonstrated by a fence-line contrast where vegetation has been heavily browsed. The map in (a) shows the location of the proof-of-concept site in South Africa, (b) shows a drone photograph of the site, with (c) showing satellite imagery and (d) the ecosystem condition for the same area calculated as the cosine distance to known natural reference sites, with greener colors indicating more closed canopy intact vegetation states 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 0.09 ± 0.04 (SD), whereas the heavily browsed side had a value of 0.32 ± 0.03 (SD), indicating a consistent increase in cosine distance from the natural reference condition under chronic browsing pressure. Notice the pseudo-savanna state of Arid Thicket on the 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. Drone image in (b) captured by Alastair J. Potts, as co-author. Satellite imagery in (c): Esri World Imagery, Maxar, acquired 08 October 2026.

Discussion

Applying the workflow in Arid Thicket showed how ecosystem-specific expert knowledge can translate available spatial data into a locally meaningful map of ecosystem condition. During Steps 2 and 3, experts identified chronic livestock browsing as the dominant pressure, described the expected degradation pathway from closed-canopy Arid Thicket towards open vegetation with reduced cover of palatable species and greater bare-ground exposure and defined and verified natural reference sites. Expert knowledge and the dominant pressure subsequently informed the selection of ecologically relevant indicators in Step 4, the interpretation of analytical outputs in Step 5, and the calibration and validation of mapped condition classes in Step 6. The mapped patterns of ecosystem condition were consistent with field studies documenting widespread browsing-induced degradation (Lechmere-Oertel et al., 2005b, 2008; Rutherford et al., 2014), while providing finer-scale spatial information than previous regional degradation mapping (Lloyd et al., 2002). Escarpment and Sundays Arid Thicket retained particularly little of their assessed natural extent in a condition resembling the natural reference state. Given recent investment in Arid Thicket restoration through the carbon-finance industry (Mills et al., 2023), the map could provide a spatial baseline for monitoring restoration and prioritizing the protection of intact remnants. Targeted field validation would nevertheless be required before site-level management decisions are made.

Nationally applied approaches such as IBECA (Jakobsson et al., 2021) and the continental HCAS (Harwood et al., 2016; Owers et al., 2026) are complementary to, rather than alternatives to, the workflow presented here. Both approaches could be implemented within Steps 4–6, whereas Steps 1–3 provide the ecosystem-specific ecological foundation for their application, by defining the natural reference state, identifying the relevant pressures and degradation pathways, and determining which ecosystem characteristics may respond. The identified pressures then provide the ecological guardrails for selecting indicators in Step 4. The principal contribution of our workflow is therefore not a new analytical method, but a reproducible process for applying suitable methods while retaining ecological meaning specific to the ecosystem and pressure being assessed.

The Arid Thicket case study demonstrated that deviation from a natural reference state can provide a data-efficient analytical pathway (Harwood et al., 2016; Jakobsson et al., 2021), where a dominant pressure produces a consistent remotely sensed response. The approach generated fine-scale, wall-to-wall estimates from a relatively small reference dataset. Unlike standardized indices such as NDVI (Pettorelli et al., 2005), the embedding metric integrated correlated surface and structural changes (Brown et al., 2025) associated with browsing, into a single distance. Cosine distance increased across expert-labelled browsing intensity classes and captured known patterns of canopy opening, supporting the selected analytical method. Similar deviation-based

approaches may be useful where reliable natural reference sites exist, and one dominant pressures exists. However, departure indicates ecological dissimilarity rather than the underlying drivers of change. Although reference-site distance was unrelated to rainfall or temperature (Appendix S3: Figure S1), departures elsewhere may reflect substrate, topography, abandoned agricultural fields, drought mortality, ecotones or vegetation-map errors. Attributing the departure from natural reference states to chronic browsing therefore depended on expert interpretation and supporting ecological evidence (Lloyd et al., 2002).

Calibration and reporting in Step 6 translated the continuous distance metric into categories that could be interpreted against expert-defined browsing intensity classes and potentially used for ecosystem accounting. In Arid Thicket, of the assessed natural extent, only 6.4% resembled the natural reference condition, 18.3% was classified as moderately browsed and 75.3% showed a condition consistent with severe browsing. If only current land cover data were still used to estimate ecosystem condition, none of this degradation would have been detected, indicating the value of tailoring a workflow to a specific ecosystem context. Although South Africa has developed condition accounts for rivers and estuaries, its published national terrestrial ecosystem accounts currently quantify ecosystem extent only rather than condition (Statistics South Africa, 2021; Xiao et al., 2024). This reflects a broader implementation gap, as condition accounts remain less developed internationally because spatially consistent, ecosystem-relevant condition data are often unavailable (Xiao et al., 2024). This workflow may thus help address this gap. The Arid Thicket assessment nevertheless represents a single-date baseline based predominantly on structural change. A complete ecosystem condition account would require repeated assessments and potentially additional indicators of ecosystem composition and function (Edens et al., 2022). Application across ecosystem types could provide a consistent procedural foundation for terrestrial condition accounts while allowing indicators and interpretation to reflect ecosystem-specific processes. The same spatial evidence could inform RLE Criteria C or D, strengthening alignment between ecosystem accounting, biodiversity reporting and restoration planning (IUCN, 2024; Xiao et al., 2024).

Pressure-specific condition assessment is especially important where several pressures co-occur, because different pressures may alter ecosystem structure, composition and function through distinct degradation pathways (Archibald et al., 2010; Keith et al., 2023; O'Connor et al., 2014). Rather than seeking a single remotely sensed metric to represent all degradation, the workflow treats each pressure–response pathway as a separate layer of ecological evidence. In fire-driven Savannas, Grasslands and Fynbos, for example, disruption of the natural fire regime should be assessed independently through assessment of fire frequency, seasonality or intensity, and associated changes in post-fire recovery (Archibald et al., 2010; Slingsby et al., 2020). Overgrazing, which often co-occurs with other pressures (Stevens et al., 2016), may be assessed through ecosystem responses as proxies, rather than direct grazing pressure alone. Relevant indicators may include bare ground exposure, loss of palatable species or reduced herbaceous cover in Step 4, analysed using fractional vegetation cover (Vermeulen et al., 2021) or climate-adjusted productivity (Lomax et al., 2025) in Step 5. Maintaining separate pressure thus layers preserves the causal reasoning connecting a pressure to changes in ecosystem structure, composition or function.

In disturbance-driven ecosystems, temporal variability or alternative stable states can obscure the relationship between deviation from natural reference states and ecosystem condition (McKellar et al., 2026). In Grasslands and Savannas, vegetation cover and productivity vary seasonally in response to rainfall, fire and herbivory (Bond et al., 2003; Higgins et al., 2023; Wessels et al., 2011), while in Fynbos vegetation, fire history, post-fire succession and climatic variability produce substantial variation among natural reference states (Slingsby et al., 2020). Consequently, a recently burnt natural reference state may differ markedly from a mature natural reference state, while a degraded ecosystem may also retain remotely sensed characteristics resembling natural reference states (McKellar et al., 2026). 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).

The Arid Thicket implementation also had limitations. First, during Steps 1–4, a single natural reference centroid represented five ecosystem types, because the natural vegetation structure was considered sufficiently similar among the included ecosystem types and the natural reference site distance showed no systematic relationship with the principal climatic gradients (Appendix S3: Figure S1). More heterogeneous ecosystems may require stratified centroids, or ecosystem-specific natural reference data or comparisons with nearest-neighbour natural reference sites. Second, the case study drew on a small group of three experts. Their agreement strengthened the reference description and labels. However, because the same experts helped define the natural reference state, labelled the browsing intensity classes and validated the map, the evaluation was not fully independent of its inputs. The validation dataset was also unbalanced (81 intact, 115 moderately browsed and 229 severely browsed sites) and was interpreted from imagery rather than measured in the field. Future applications could reduce this dependency by obtaining validation data from experts or field observers not involved in setting the natural reference state, following the structured elicitation guidance in the RLE guidelines (IUCN, 2024). Expertise is also unevenly spread across South Africa's biomes, so the depth of expert input behind each assessment should be reported with its results, as we did for this case study.

Uncertainty assessment and validation in Step 6 remain essential regardless of the indicator or analytical method selected (Singh et al., 2024). The bootstrap uncertainty analysis showed that condition estimates were relatively insensitive to resampling of the available natural reference sites across most of the study area, providing a measure of how consistently condition can be estimated given variability in the natural reference baseline. However, the bootstrap captures only uncertainty from sampling the natural reference sites. It does not capture uncertainty in the embeddings, the thresholds or expert labelling, which should also be quantified explicitly where possible. In ecosystems where the remotely sensed signal of natural vegetation varies strongly within or between years, or after natural disturbances such as fire, uncertainty may be substantially higher and more difficult to interpret. Quantitative validation therefore needs independent field-derived data. In Arid Thicket, suitable measures may include canopy and bare-ground cover from line- or point-intercept transects, cover of *P. afra* and other palatable succulents, and drone-derived canopy cover. These can be compared with cosine distance using

rank correlation or ordinal classification accuracy. Where such measurements are impractical, independent expert condition scores from field visits or from geolocated landscape photographs (e.g., on a 1–5 scale) are a practical alternative (Bell et al., 2022). Photographs allow several experts to score the same sites independently, without seeing the map, thus agreement among raters can also be quantified. Long-term monitoring applications will also require periodic updating of reference and training datasets (Woodcock et al., 2020), as ecosystem states change over time due to land use, disturbance and ecological succession. Further application for monitoring could also test whether annual embeddings are consistent between years, before changes in distance are interpreted as changes in condition. Developing efficient approaches for maintaining and updating these datasets (Fonseca et al., 2021) remains a key research priority.

Conclusion

Using the Arid Thicket as a case study, we demonstrate that the workflow provides a consistent but flexible foundation for ecosystem condition assessment in South Africa by standardizing the decision-making process rather than prescribing universal indicators or analytical methods. Its strength lies in placing ecosystem-specific knowledge and experts at the centre of defining natural reference states, degradation pathways and meaningful measures of ecological change. By translating this knowledge into scalable spatial products, the workflow can support ecologically defensible condition accounting, biodiversity reporting and restoration planning across diverse ecosystems and data contexts.

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Author contributions

SVDM, ALS, VV, CLS, MTH, GRM, JAS, JS, AJP conceived the ideas and designed the methodology; SVDM, ALS, MP, ARP 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.

Conflict of Interest Statement

We declare no conflict of interest.

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Journal: Ecological Applications

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

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Appendix S1

IUCN T1.2.1: Arid Thicket

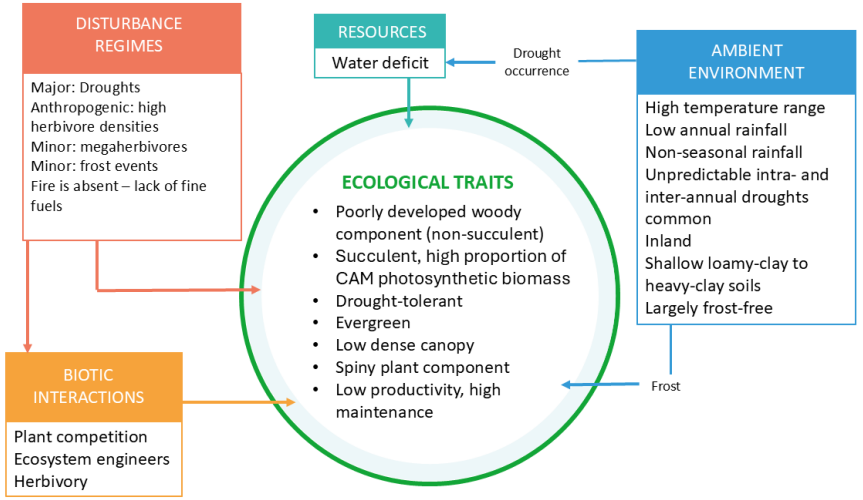
Biome: Albany Thicket, South Africa

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.

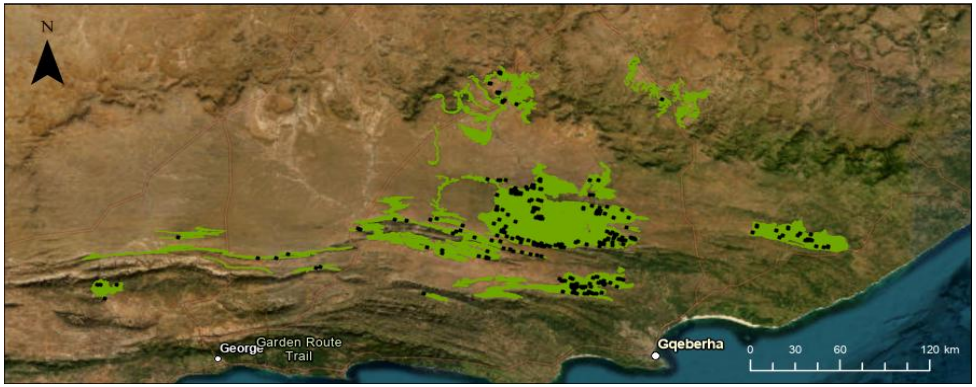
Arid Thicket has a low fine fuel load (e.g. lacks grasses), making it largely fire-excluding under intact and degraded conditions. Key biotic interactions include plant competition for scarce water, especially among shallow-rooted succulents. Ecosystem engineers like *P. afra* and *Euphorbia* spp. play 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.



Arid Thicket

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 (Fig 1). 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.



References used to create Appendix S1

Cowling, R., Proches, S., & Vlok, J.H.J. (2005) On the origin of southern African subtropical thicket vegetation. *South African Journal of Botany, 71(1)*, 1–23. https://doi.or/10.1016/S0254-6299(15)30144-7

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Journal: Ecological Applications

Appendix S2: 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, Michael Powell, Anthony R. Palmer and Andrew L. Skowno

Table 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

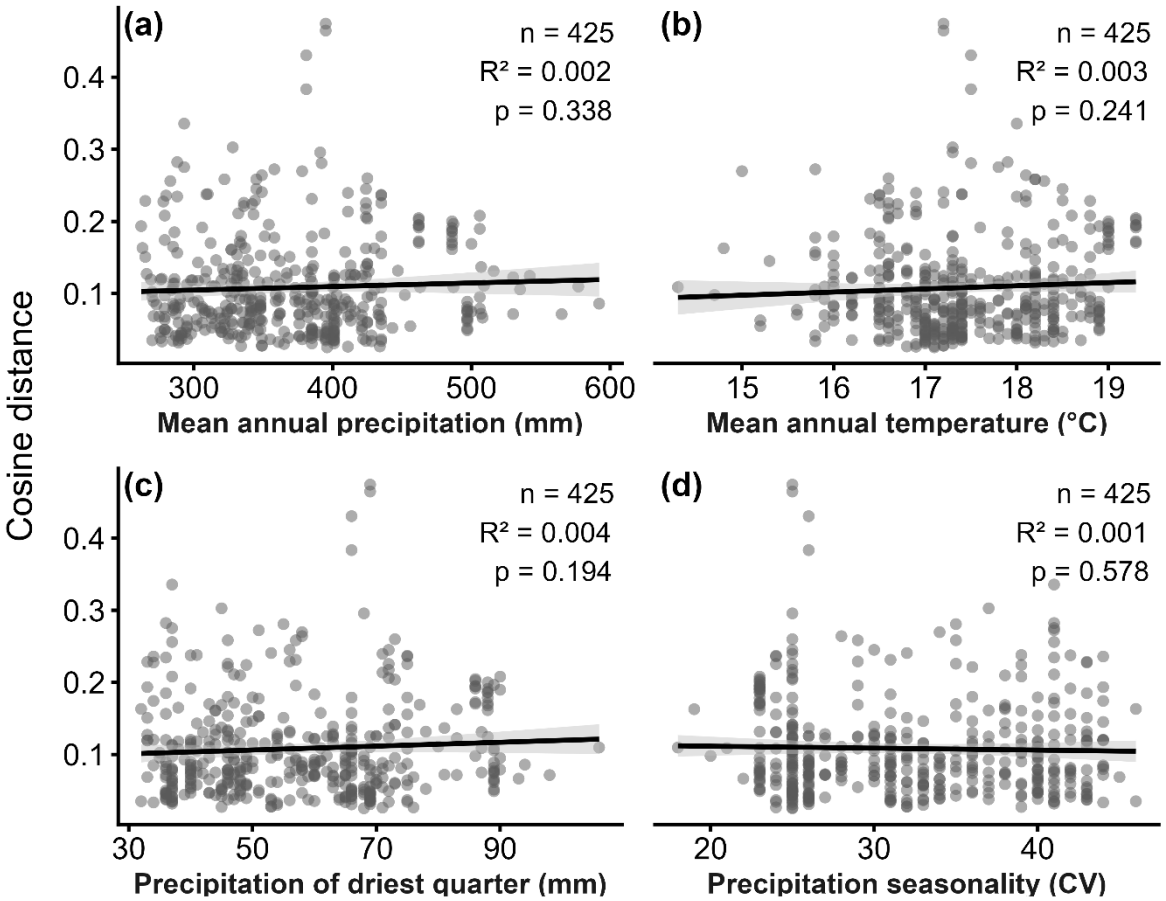
Table S2. Examples of ecological indicators and remote sensing metrics for each of the key pressures in South Africa. Note this is not an exhaustive list of indicators and metrics, but is intended to guide Steps 4 and 5 of this workflow. The selection is dependent on the ecological context of the study 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

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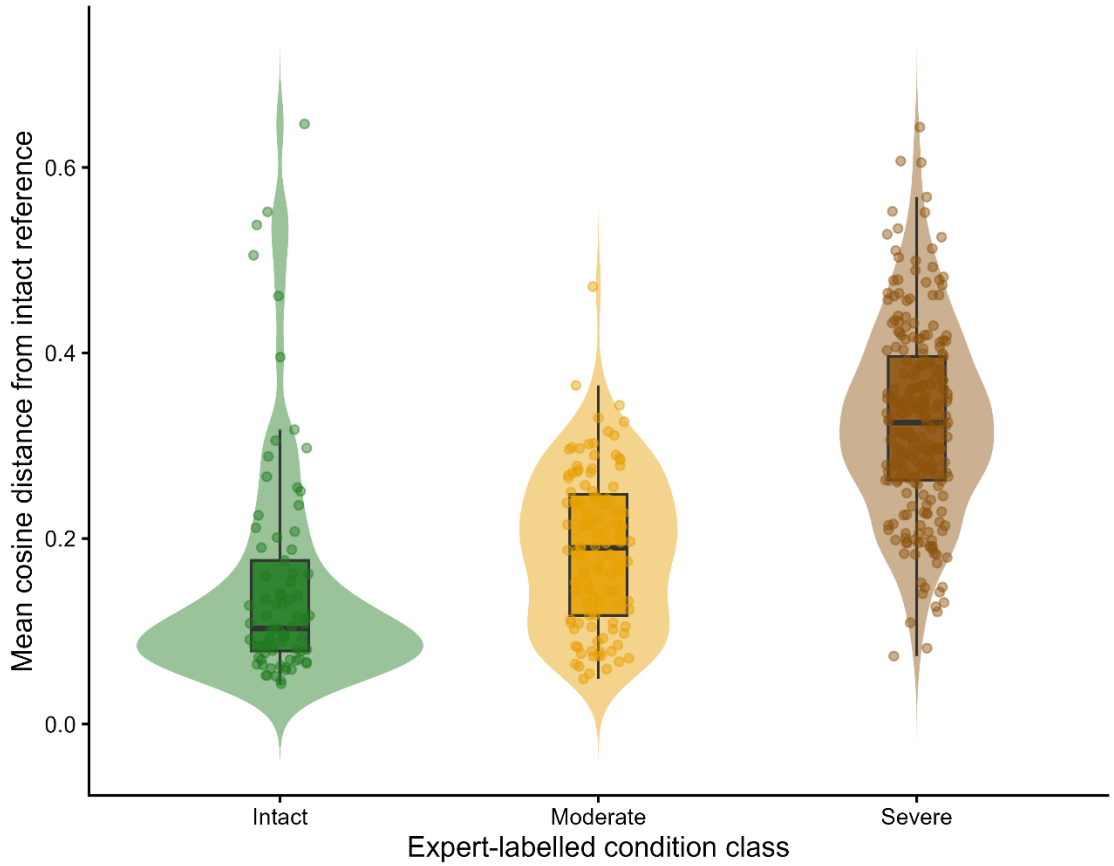


Figure S2. Relationship between expert-labelled browsing labels and cosine distance from the natural reference Arid Thicket sites. Violin plots show the distributions of the 2025 bootstrap mean cosine distance extracted at expert-labelled intact (i.e. natural herbivory), moderately overbrowsing and severely overbrowsed locations. Higher values indicate greater deviation from the intact reference centroid.

Table S1. Area and proportion of the assessed natural extent assigned to each ecosystem condition class within Arid Thicket ecosystem types.

Ecosystem type	Assessed area (ha)	Intact ha (%)	Moderate ha (%)	Severe ha (%)
Albany Arid Thicket	1,449	1,088 (75.1)	274 (18.9)	86 (6.0)
Escarpment Arid Thicket	122,889	1,978 (1.6)	20,028 (16.3)	100,883 (82.1)
Fish Arid Thicket	62,512	12,981 (20.8)	25,747 (41.2)	23,785 (38.0)
Gamka Arid Thicket	48,307	3,361 (7.0)	12,105 (25.1)	32,842 (68.0)
Sundays Arid Thicket	552,114	31,071 (5.6)	86,040 (15.6)	435,003 (78.8)
All Arid Thicket	**787,272**	**50,479 (6.4)**	**144,194 (18.3)**	**592,599 (75.3)**

Percentages are calculated relative to the assessed remaining natural extent of each ecosystem type. Intact represents cosine distances ≤0.140, Moderate represents values >0.203 and <0.256, and Severe represents values ≥0. 0.256. These categories were developed as an illustrative application for ecosystem condition accounting.