Received: 21 January 2025 | Revised: 15 June 2026 | Accepted: 15 June 2026

DOI: 10.1111/csp2.70351

CONTRIBUTED PAPER

Conservation Science and Practice
A journal of the Society for Conservation Biology
Open Access

WILEY

Evaluating a strategic approach for identifying and ranking holistic sets of indicators of conservation project success

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Funding information

Australian Research Council Future Fellowship, Grant/Award Number: FT170100279; Australian Government Research Training Program Scholarship; Noosa Biosphere Reserve Foundation

Abstract

Evidence-based conservation often fails to balance ecological and socioeconomic measures of success. Indicator selection is often biased by expert opinion, misaligned with goals, and lacks scientific rigor. We developed and tested the Holistic Indicator Selection Protocol (HISP), a semi-systematic approach to improve indicator prioritization in conservation planning. Based on the widely adopted Conservation Standards, HISP combines expert and stakeholder input with structural situation model parameters to identify and rank ecological and socioeconomic candidate indicators relevant to evaluating conservation success. In a case study landscape with typical conservation challenges, we applied four HISP indices to score indicators based on their effectiveness at representing: (1) conservation threats; (2) project strategy defined by a situation model; (3) expert opinion; and (4) stakeholder opinion. We statistically evaluated each index for its ability to minimize selection biases and complexity. Indicators represented ecological and socioeconomic dimensions, direct and indirect threats, and governance strategies. The threat-based index prioritized socioeconomic challenges, whereas the model-based index balanced socioeconomic and ecological indicators, suggesting broader applicability. Opinion-based indices introduced some biases but remained valuable for data-limited contexts. HISP offers a transparent, adaptable method for prioritizing conservation indicators—supporting rather than replacing expert judgment—enabling refinement based on feasibility and conceptual alignment.

KEYWORDS

conceptual model, conservation management, experts, project evaluation, stakeholders, strategic planning, threat assessment

1 | INTRODUCTION

Failure of the Convention on Biological Diversity (CBD) to halt biodiversity decline by 2020 has been partly attributed to inadequate consideration of policy frameworks, socio-economic drivers, and indicators of conservation success (Leclère et al., 2020; Nicholson et al., 2021; Xu et al., 2021). Conservation science has often not leveraged action, as it mostly under-represents social dimensions and rarely involves practitioners or planning for implementation (Bennett et al., 2017; Knight et al., 2008). Although evidence-based conservation planning has emerged to address these deficiencies (Pullin & Knight, 2009; Sutherland et al., 2004), little scientific evaluation exists on its effectiveness (Bottrill & Pressey, 2012; McIntosh et al., 2018). Furthermore, while there are now thousands of examples of conservation evaluations utilizing data on management effectiveness worldwide, relatively few use data from detailed monitoring (Coad et al., 2015), despite this latter more quantitative and outcome-driven approach being more appropriate to demonstrating conservation success (Ribas et al., 2020).

The integration of ecological and socioeconomic "indicators" (defined in glossary of terms; see Table S1) is widely endorsed for managing ecosystems sustainably (Table S2). This approach strengthens the evidence basis for decision-makers to assess the effectiveness of conservation actions (Ferraz et al., 2022). This is particularly important in developing countries, where broad-scale socioeconomic factors drive environmental degradation (Bradshaw & Di Minin, 2019). However, conservation projects rarely measure ecological and socioeconomic indicators concurrently (Loveridge et al., 2020; Mansourian & Vallauri, 2022), and despite the influence of social dimensions on conservation success, socioeconomic datasets remain scarce compared to ecological ones (Ferraz et al., 2022; Wortley et al., 2013). Consequently, genuinely holistic research evaluating both ecological and socioeconomic aspects of conservation remains rare, and standardized frameworks for selecting holistic sets of indicators are seldom applied in decision-making.

The socioeconomic oversight in conservation science leads to under-quantified biodiversity threats, with ultimate causes (i.e., indirect threats such as economics, policy, infrastructure, culture, and education) being less understood than proximate causes (i.e., direct threats like human activities). Consequently, conservation science struggles to effectively inform threat management. A global review (1997–2017) found that while 43% of studies assessed proximate causes, only 10% linked them to ultimate drivers (Williams et al., 2020). Evaluating threats alongside key ecological indicators is essential for measuring conservation success but remains uncommon. Unlike most scientific studies, planning frameworks inherently include full threat assessments (e.g., Kapos et al., 2008; Conservation Measures Partnership [CMP], 2020; Table S2). Integrating these frameworks into conservation science and indicator selection could mitigate proximate bias and bridge the science-implementation gap (Schwartz et al., 2018), thus providing valuable scientific input to conservation practice.

Selecting appropriate indicators remains challenging given the hundreds of potential options available (Table S2), particularly under limited conservation resources (Kapos et al., 2008). Consequently, indicator selection is often biased by expert opinion, lacks scientific rigor, and is poorly aligned with conservation goals (Dale & Beyeler, 2001). While expert opinion is valuable, it must be applied within structured frameworks to ensure defensibility (Janoušková et al., 2018). Although most conservation planning frameworks offer indicator guidance (Table S2), systematic selection approaches are scarce and have only recently emerged (Bal et al., 2021; Game et al., 2018), with limited empirical evaluation of indicator selection biases.

Here, we introduce and evaluate the Holistic Indicator Selection Protocol (HISP), a novel approach for identifying and ranking conservation indicators. HISP uses a semi-systematic method to identify and rank socioeconomic and ecological indicators of conservation success, reducing traditional biases and enhancing scientific rigor in conservation monitoring. To ensure global relevance for conservation management, the HISP is framed around the widely-used Conservation Standards (CMP, 2020)—an open-source framework developed by a consortium of international organizations to unify conservation planning, management, and monitoring with common tools and terminology. Despite its widespread use in conservation planning, this framework has rarely been incorporated into scientific investigations. In this paper, we present the HISP framework using an East African tropical forest case study to identify candidate ecological and socioeconomic indicators of conservation success and calculate four alternative HISP indices to rank their relative importance. We then assess the relative merits of these indices and discuss how practitioners may benefit from applying the HISP framework in conservation monitoring. By integrating planning frameworks and participatory approaches, the HISP aims to advance evidence-based decision-making in conservation science, policy, and practice, narrowing the science-implementation gap. The method is applicable to ecosystem- or species-focused conservation projects and is tested here using a tropical forest case study with challenges typical of high-biodiversity regions globally.

2 | MATERIALS AND METHODS

2.1 | Overview and case study

The procedure for completing the HISP approach comprised four steps for identifying candidate indicators, followed by three steps for ranking them (Figure 1—steps 1–7). From this, our intention is for conservation project teams to consider this relatively unbiased, strategically developed information, against more practical considerations such as available time, expertise, and resources, to produce a well-informed monitoring plan (Figure 1—steps 8–10).

As a case study for implementing this approach, we selected a threatened, high biodiversity forest mosaic, the Magombera Conservation Area, in Tanzania (Figure S1). Besides representing conservation challenges typical of developing regions, for example, limited resources, low income and livelihood development needs, this case study was also a good candidate for the first trial of the HISP approach, because it had a single over-arching "target" of conserving forest ecosystem health. This was preferable to a species-specific target, or multi-target project, to ensure relevance for both biodiversity and livelihoods, while also reducing complexity. The case study also included an established science–management partnership and participatory planning process. The conservation program had been operating for 5 years, working with the Tanzanian Government and nearby communities to address local environmental challenges and to protect and monitor the site.

2.2 | Identification of candidate indicators

Our procedure for identifying candidate indicators followed the Conservation Standards approach for developing a "situation model" (or "conceptual model"; CMP, 2020). The first step in developing a situation model is to select a project team, who for this study

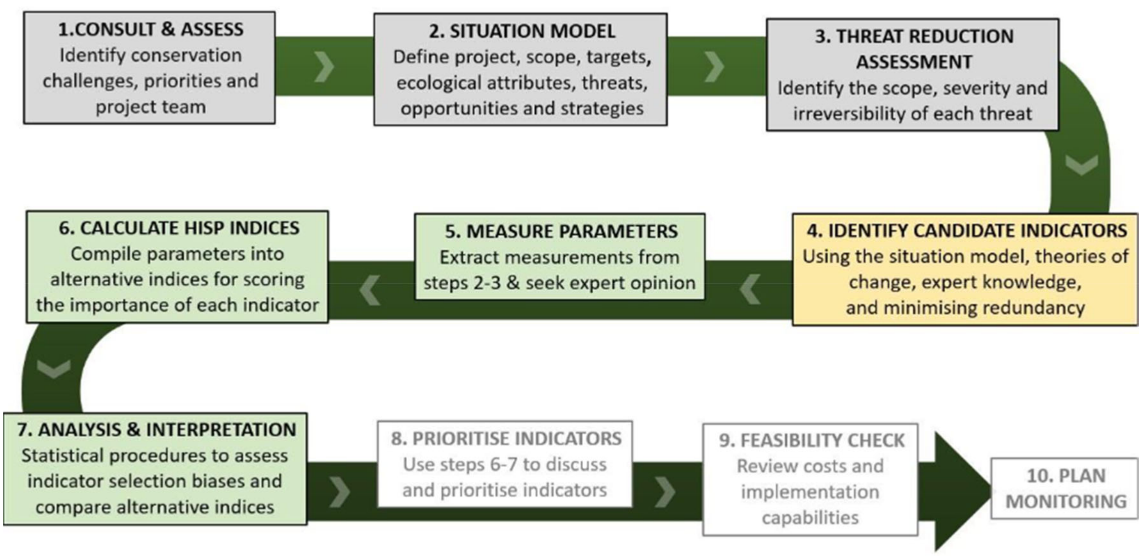

FIGURE 1 Workflow of the Holistic Indicator Selection Protocol (HISP) for identifying and ranking candidate conservation indicators. Steps 1–3 (gray) follow the Conservation Standards (CMP, 2020). Step 4 (yellow, adapted from the Conservation Standards) and Steps 5–7 (green, newly developed) comprise the HISP method implemented in this study. Steps 8–10 (white) outline the subsequent phases—refining indicator selection and planning implementation—which are not part of this case study but are addressed in follow-up applications (e.g., Oliveira et al., in prep.).

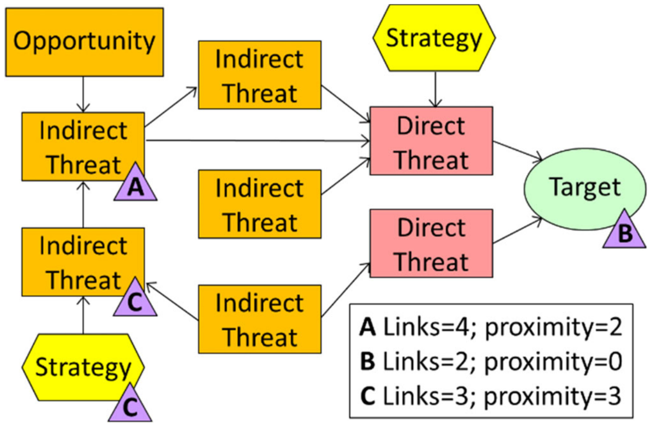

FIGURE 2 Schematic showing the basic structure of a Conservation Standards (CS) situation model (or "conceptual model"; CMP, 2020). All components are labeled and our two parameters used for the HISP calculation are shown for indicators A–C: *Links* refers to the total number of links (arrows) joining factor(s) measured by each indicator; *Proximity* = minimum number of links between the target and the same factor(s). Factor colors and shapes follow the Miradi 4.0 software (target = pale green; direct threat = pink; indirect threat = amber; strategy = yellow). A full situation model using this structure for our case study can be found in SI5.

comprised three of the coauthors—a manager, a sociologist, and a biologist (Table S3). The team then completed the remaining elements of the situation model, including identification of the conservation scope, vision and targets, direct and indirect threats, opportunities, strategies, and their interactions—these approaches are well-established and outlined in Table S3. As per Conservation Standards procedure, the situation model was illustrated as a flow chart (Figures 2 and S2), with directional links connecting "factors" with influence on the conservation target (Table S3).

The next step was to carry out Threat Reduction Assessment (TRA)—an approach used worldwide for measuring conservation success in terms of project outcomes (Salafsky & Margoluis, 1999) and integral to the Conservation Standards. TRA involves the quantification of three measurements of each threat in a situation model, which together represent the overall importance of each threat for conservation management. The first measurement, "scope," estimates the proportion of the overall case study area affected by each threat. The second measurement, "severity," estimates the proportion of the conservation target that could be eradicated as a result of each threat. The third measurement, "irreversibility," estimates the proportion of the effect on the target that could not feasibly be reversed by the project strategies. These three measurements were informed by the project team's expertise, along with published and unpublished data from the case study site.

Using the information gathered in preceding steps, the team then identified candidate indicators relevant to evaluating conservation success (Table S4). Firstly, ecological indicators were identified using the Conservation Standards approach for defining the conservation target using "Key Ecological Attributes" (KEAs) (CMP, 2020; Parrish et al., 2003; SI6). KEAs were used to represent flagship species, expected ecological impacts of each direct threat, and measures of ecosystem status including biodiversity, biomass, habitat structure, soil quality, habitat connectivity, and a pre-existing index for summarizing the combined progress of all indicators towards project expectations (Holistic Ecosystem Health Index; Aguilar, 1999). The team then identified indicators useful for evaluating the progress of each strategy and objective towards reducing threats. In determining these indicators, particular focus was placed on indicators that: (1) had high TRA scores, (2) corresponded to critical management intervention points for addressing key threats in the situation model, and (3) were not already represented by other indicators, thus maximizing relevance while minimizing redundancy. All candidate indicators were required to be measurable, sensitive, and consistent in definition and importance over time (Margoluis & Salafsky, 1998).

2.3 | Indicator ranking

The remaining steps 5–7 are novel to the HISP approach (Figure 1), for which we developed four alternative HISP indices for ranking the importance of each indicator. Each HISP index was calculated from an alternative set of parameters, described below for each index. These parameters were derived either from the situation model, or from expert and other stakeholder opinion, with those known by the project team to have the most serious consequences for the target given a double weighting. The parameters were selected such that the four alternative indices described below were scored based on (1) Threat Reduction Assessment (H_{TRA}), (2) the Conservation Standards (H_{CS}), (3) expert opinion (H_X), and (4) equality of opinions (H_E). Each index was calculated as a percentage of the maximum possible value, that is, assuming that every parameter of the index was maximized. While these four versions of the HISP index were used by the Magombera Conservation Area case study, we emphasize that different projects might place alternative weight on different parameters, depending on project priorities and the reliability of information within each parameter.

2.3.1 | HISP index 1: H_{TRA}

This index was formulated as an estimate of the relative threat level to the conservation target represented by each indicator. Indicators were scored based on measurements derived and adapted from the case study TRA. The calculation was as follows:

$$H_{\mathrm{TRA}} = (\text{scope} + [2 \times \text{severity}] + \text{reversibility}) \div 4 \quad (1)$$

where the three parameters comprised (a) *scope*—the percentage of the case study site land area relevant to the indicator, (b) *severity*—the upper estimate of the expected percent reduction in the target represented by the indicator over 10 years without project intervention, expressed as the percentage of the highest severity indicator; and (c) *reversibility*—the percentage of the expected reduction in the target that could feasibly be reversed by long-term project activities (50 years). The latter measurement is the inverse of the irreversibility score in TRA, to maintain consistency with other parameters, for which high scores represent high potential for indicators.

For example, the charcoal kiln indicator represented tree removal for fuel production. *Scope* was estimated as the proportion of the landscape with woody vegetation, *severity* reflected the potential biomass loss from charcoal extraction, and *reversibility* reflected the feasibility of mitigation through alternative fuel incentives.

2.3.2 | HISP index 2: H_{CS}

Due to an explicit bias toward threats in H_{TRA}, we modified this index to represent the key ecological attributes and the situation model more explicitly, resulting in a less subjective index that makes more direct use of the overall Conservation Standards strategic planning procedure. Therefore, for this index, we added two parameters derived from the situation model, quantifying indicator representation of multiple factors and direct measurement of the target. The calculation was as follows:

$$H_{\mathrm{CS}} = (\text{scope} + [2 \times \text{severity}] + \text{reversibility} + \text{links} + \text{proximity}) \div 6 \quad (2)$$

where the parameters were consistent with Equation (1), plus (a) *links*—the number of situation model links connecting the factor(s) or target(s) measured by each indicator to other factors or strategies, and (b) *proximity*—the minimum number of links connecting each indicator to the target (Figure 2). Both were expressed as percentages of the highest number, with *proximity* inversed so that indicators closest to the target scored 100%. Links were not double-counted for indicators measuring more than one factor, and only those relevant to each indicator were counted.

2.3.3 | HISP index 3: H_{X}

Evaluation may benefit from impartial external input and participatory approaches (Hockings et al., 2006). We therefore modified H_{CS} to incorporate the opinions of experts and other stakeholders. The result was a simplified indicator scoring process, achieved through the exclusion of quantitative threat assessment, based on the assumption that expert and stakeholder opinions already partially reflect perceived threat. We also increased the weight of the *links* parameter to ensure continued situation model representation and expert opinion because of their broader knowledge of conservation planning and monitoring over other stakeholders (although see H_{E}). This was calculated as follows:

$$H_{\mathrm{X}} = (\text{proximity} + [2 \times \text{links}] + [2 \times \text{expert}] + \text{stakeholder}) \div 6 \quad (3)$$

where two novel parameters from Equations (1) and (2) comprised (a) *expert*, and (b) *stakeholder*, which were relative importance scores for each indicator, ranging from 1 (not important) to 9 (very important), according to professionals or local communities, respectively. These scores were expressed as a percentage, from 0 (lowest score given) to 100 (highest score given). *Stakeholder* was defined as the median score decided by a majority vote by four local village committees. To prioritize expert knowledge from within the project team, the *expert* parameter was calculated as follows:

$$\text{expert} = \text{median}\left(\text{project}_{i}, \text{project}_{ii}, \text{project}_{iii}, \text{median}[\text{external}_{i-iii}]\right) \quad (4)$$

where *i*–*iii* were three professionals from each of (a) the project team and (b) other external organizations, with a combined total of 62 years of conservation experience in Tanzania, yet without firsthand experience of the case study site. To create a balanced perspective within the project team, the external experts included a biologist, a social scientist (sociologist, SS), and a charity director (manager, CM). Both experts and other stakeholders were briefed on the nature and rationale for each indicator prior to deciding their scores (Table S4). All other parameters were consistent with Equation (2).

2.3.4 | HISP index 4: H_E

Local stakeholders are important and often overlooked in conservation planning, plus we have already emphasized existing ecological bias. The final index was therefore designed to be less biased than H_X through equal weighting of expert and other stakeholder opinions and removal of ecological bias by excluding the proximity parameter. This was calculated as follows:

$$H_E = (\text{links} + \text{expert} + \text{stakeholder}) \div 3 \quad (5)$$

where all parameters were consistent with Equations (2) and (3).

2.4 | Data analysis

Data analysis aimed to ensure scientific rigor through statistical evaluation of our HISP approach and to guide future users in selecting between (or adapting) the four HISP indices. To achieve this, we tested three assumptions that an ideal HISP index would be expected to fulfill: (1) minimize "indicator ranking bias" by assigning high weight to some indicators across all categories (ecological, socioeconomic, and cross-cutting) and situation model stages (conservation target, direct and indirect threats); (2) demonstrate "index parity," that is, broadly representing the alternative HISP indices; and (3) be "parsimonious," that is, ensuring that all HISP index parameters contribute independently to the index, while effectively representing the situation model (links, proximity) and TRA parameters (scope, severity, reversibility), regardless of their explicit inclusion.

2.4.1 | Indicator ranking bias

We first assessed indicator effectiveness in reducing traditional bias towards ecological indicators and direct threats. We assessed how well indicators represented the whole situation model (stage bias) by quantifying the number of indicators within each stage (target, direct threat, indirect threat). We categorized each indicator as "ecological" (the KEAs, as defined above), "social" (relating to human livelihoods), "economic" (relating to income or cost), "governance" (relating to legislation or management), or "cross-cutting" (relating to two or more categories) (Table S4). To summarize individual indicator bias, we identified (a) the top-scoring indicator for each HISP index and for the mean across all four HISP indices, and (b) the most consistently important indicators, scored in the top 25% and 50% by each index. Additionally, we assessed situation model stage and category bias in indicator rankings between indices and their parameters, as well as expert and other stakeholder opinions. We compared the mean score per indicator between each category/stage using (a) ANOVA and Tukey post hoc tests for each index, and (b) Kruskal–Wallis and Dunn post hoc tests for each parameter and group of experts, with the latter's data being mostly skewed, leading to the use of non-parametric methods.

2.4.2 | Index parity

Index parity was identified by determining how well each HISP index represented the others. To determine variation between HISP indices and the mean across all indices, we counted the number of shared indicators among the top 25% and 50% ranked indicators. We calculated Pearson correlation coefficients to further assess variation in indicator ranks between all pairwise combinations of indices.

2.4.3 | Parsimony

To assess our third and final measure of index suitability, we determined the relative contribution of each parameter to the four HISP indices, and hence the importance of each parameter. We used Pearson correlation tests to compare all parameters to each index, including parameters explicit to each index plus those from the remaining indices. Non-explicit parameters were included to determine the extent to which each was represented by intercorrelation with other parameters, and hence their unique contribution to index scores. We then used multiple regression (Gaussian Generalized Linear Model—GLM) to compare the independent contribution of all index parameters to each HISP index.

To further assess uniqueness and inter-correlation, for each HISP index parameter (transformed as needed to reduce skew) we calculated (a) Pearson correlation versus all other parameters, and (b) overall correlation versus all other parameters, using Variance Inflation Factors (VIF), with VIF < 2.0 indicating minimal intercorrelation (Zuur et al., 2010). These results included correlation between expert and other stakeholder opinions and the situation model/TRA parameters (indicating the reliability of opinions for replacing the semi-systematic measures). We used a Gaussian GLM multiple regression analysis to determine the influence of situation model/TRA parameters (both separately and averaged) on mean stakeholder, manager, sociologist, biologist and academic (mean biologist and sociologist) scores. Finally, to determine the independent contribution of different experts and other stakeholders, we employed Spearman correlation (due to highly skewed data) to compare indicator scores by (a) expertise (biology, sociology, management, local community stakeholder), (b) academics versus non-academics, and (c) project team versus external.

False Discovery Rate (FDR) endpoint adjustment was used for all repeat testing (Benjamini & Hochberg, 1995).

3 | RESULTS

3.1 | Indicator ranking bias

We identified 44 candidate indicators representing all four situation model stages (Figure 3; Table S5) and five indicator categories (16 ecological; 17 socioeconomic [10 social, 4 economic, and 3 governance]; 11 cross-cutting; SI6). The four HISP indices showed little bias, mostly scoring indicators approximately equally across categories and stages (Figure 4; H_{CS}, H_X, and H_E: $p \geq .27$, $F \leq 1.34$). Socioeconomic indicators, particularly governance-related, scored higher than ecological in H_{TRA} ($p = .015$–0.029, $F = 3.54$–3.87; Table S6). The H_E index showed the least variation in scores across categories and stages (standard deviation of index scores 1.1 and 2.5, respectively), followed by H_{CS} (2.6, 3.5), H_X (3.8, 6.6), and H_{TRA} (8.9, 3.8).

The top-ranked indicator on average, particularly for H_{CS}, was the perceived natural resource deficit among local communities, which is a socioeconomic indirect threat (Table 1). The highest H_{TRA} indicator was also a socioeconomic indirect threat (forest legal status), whereas for H_X and H_E, it was an ecological measure (forest area). Three indicators occurred in the top 25% across all HISP indices, including wildfire prevalence, aboveground biomass, and forest-derived community income. Those indicators in the top 50% also included a cross-cutting indirect threat (community conservation compliance), ecological measures (pole and timber-sized tree stems and keystone monkey population density), socioeconomic indirect threats (forest legal status and forester

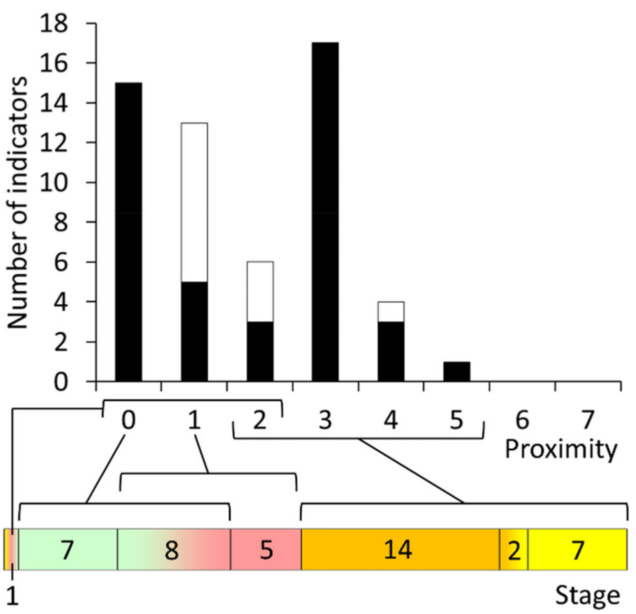

FIGURE 3 Spread of indicators across our situation model. The bar chart shows the proximity of indicators to the conservation target (i.e., the number of steps [maximum 7] between the relevant factor and the target). Black bars show indicators included for the first time at each step, and white bars show indicators that have already been included in previous steps. The colored bar shows the number of indicators representing different situation model stages (target = pale green; direct threat = pink; indirect threat = amber; strategy = yellow; graded bars show indicators representing more than one stage).

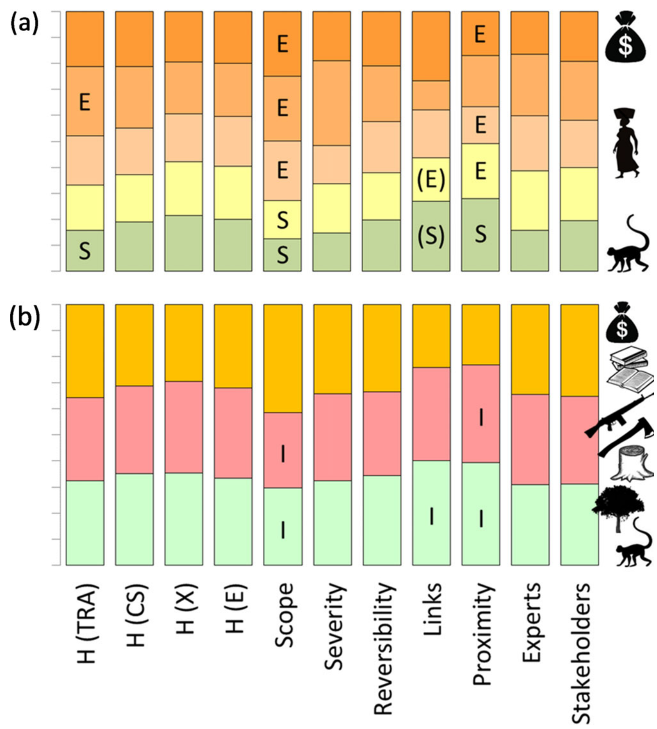

FIGURE 4 Relative mean rankings (scaled to 100% on the *y*-axis) of four HISP indices and their seven parameters, per (a) category [ecological = green; cross-cutting = yellow; socioeconomic = orange {subcategories: Social = pale, governance = mid, economic = dark}] and (b) situation model stage [target = pale green; direct threat = pink; indirect threat = amber]. Letters indicate categories or stages with significantly different (or near significant, i.e. $p \leq .05$ but not $\leq \alpha_{FDR}$) indicator scores than socioeconomic "S," ecological "E" or indirect threat "I" indicators from Tukey/Dunn post hoc tests (Tables S6, S8, and S9).

TABLE 1 HISP indices for the highest priority indicators of conservation success (top 50%).

Indicator (see SI5)	Category	Stage	H_{TRA}	H_{CS}	H_X	H_E	Mean
Natural resource needs	Socioec-s	I	90.0	**86.2**	88.3	90.9	88.9
Wildfires	Cross-cut	D	92.5	82.4	77.1	79.5	82.9
MoU compliance	Cross-cut	I	95.0	79.3	72.3	79.5	81.5
Above-ground biomass	Ecological	T	80.8	78.2	82.1	82.1	80.8
Forest income	Socioec-e	I	88.8	76.4	74.9	82.1	80.5
Timber-sized tree stems	Ecological	TD	70.8	77.9	83.8	83.8	79.1
Forest legal status	Socioec-g	I	**100.0**	82.4	64.0	68.8	78.8
Pole-sized tree stems	Ecological	TD	80.8	83.3	76.7	72.1	78.2
Monkey population density	Ecological	T	80.8	80.8	74.6	73.0	77.3
Holistic Ecosystem Health Indicator	Cross-cut	T	85.0	84.9	73.1	56.4	74.8
Tree-cutting	Cross-cut	D	78.3	75.4	71.1	73.5	74.6
Forest management training	Socioec-g	I	90.0	73.2	64.5	69.2	74.2
Forest area	Ecological	TD	46.0	60.2	**92.3**	**92.3**	72.7
Community knowledge	Socioec-s	I	53.8	58.2	85.2	**92.3**	72.4
Charcoal kilns	Cross-cut	D	68.3	66.2	75.6	76.5	71.6
Physical/mental wellbeing	Socioec-s	I	88.8	77.7	55.3	62.4	71.0
Stakeholder awareness	Socioec-s	I	65.0	58.2	72.5	82.1	69.4
Patrols	Socioec-g	I	88.8	75.1	48.6	54.2	66.7
Rare tree species	Ecological	TDI	65.0	67.7	63.9	62.4	64.7
Village tree sustainability	Cross-cut	I	60.8	60.1	66.2	70.9	64.5
Forest regeneration	Ecological	TDI	42.0	53.6	81.6	78.6	64.0
Soil quality	Ecological	T	55.8	65.4	67.5	67.5	64.0

Note: The top-ranked indicator for each index is shown in bold. Shading shows the top 25% (orange) and 50% (yellow) indicators for each index, respectively. Socioeconomic (socioec) subcategories: e = economic; g = governance; s = social. Stages: D = direct threat; I = indirect threat; T = target. Indices for the full set of indicators are given in Table S7.

training), and cross-cutting direct threats (tree-cutting frequency and charcoal removal).

The seven parameters of the HISP indices varied significantly in their level and direction of indicator ranking bias (Figure 3; Kruskal–Wallis: $p = .00–.99$; $\chi^2 = 0.0–41.2$). Among the TRA-derived HISP index parameters, socioeconomic and governance indicators generally had high scores for scope, severity, and reversibility, with indirect threat indicators also showing high scope (Figure 4; Table S8). Situation model-derived parameters (links, proximity) were relatively high for ecological and target indicators, while economic indicators also had high linkage (Figure 4; Table S8). Indicator ranking bias between ecological and socioeconomic categories, and situation model stages, was low among the experts and other stakeholders, who largely agreed with one another (Figure 4; Table S9). Ecological indicators received significantly reduced scores from academics, and even biologists scored them lower than non-academics, although not to a significant degree (Table S9).

3.2 | Index parity

The four HISP indices shared 4 (36%) and 12 (55%) indicators in the top 25% and 50%, respectively (Table 1). The H_{CS} index showed the most parity, with 91% and 86% overlap with the mean among the top 25% and 50% indicators, respectively (Table 1), followed by H_X, H_{TRA}, and H_E (Tables 1 and S7). All indices showed significant covariance; the highest between H_X and H_E (89%), and H_{TRA} and H_{CS} (78%) (Table 2; Figure S4). The H_{CS} index again showed the greatest parity through (a) high correlation with the mean (SI6.6) and (b) high mean correlation with other indices ($r^2 = 0.49$), followed by H_X ($r^2 = 0.48$), H_E ($r^2 = 0.44$), and H_{TRA} ($r^2 = 0.36$).

3.3 | Parsimony

The HISP indices with more parameters (H_{CS}, H_X) correlated with five of the seven parameters compared with

TABLE 2 Relationship between the four HISP indices and their seven parameters, including Pearson r^2 (and proportion deviance explained by a full GLM; Table S10) above the diagonal, and direction of trend below the diagonal ("+" and "–" = significant positive and negative trends; "0" = no significant trend [$r^2 < 0.05$]; $\alpha_{FDR} = 0.025$).

	H_{TRA}	H_{CS}	H_X	H_E	Scope	Severity	Reversibility	Links	Proximity	Experts	Stake-holders
H_{TRA}		0.78	0.14	0.16	0.54 (0.07)	0.83 (0.32)	0.07 (0.02)	*0.01 (N)*	*N (N)*	*0.25 (N)*	*0.02 (N)*
H_{CS}	+		0.40	0.29	0.29 (0.05)	0.74 (0.24)	0.06 (0.02)	0.26 (0.05)	0.12 (0.03)	*0.21 (N)*	*0.01 (N)*
H_X	+	+		0.89	*0.02 (N)*	*0.21 (N)*	*0.01 (N)*	0.47 (0.18)	0.19 (0.01)	0.55 (0.25)	0.12 (0.04)
H_E	+	+	+		*0.04 (N)*	*0.21 (N)*	*0.02 (N)*	0.30 (0.19)	*0.03 (NA)*	0.57 (0.21)	0.32 (0.16)
Scope	+	+	0	0		0.19	0.05	N	0.16	0.15	N
Severity	+	+	+	+	+		N	0.02	0.01	0.26	0.04
Reversibility	0	0	0	0	0	0		N	N	0.02	0.02
Links	0	+	+	+	0	0	0		0.28	0.02	N
Proximity	0	+	+	0	−	0	0	+		N	0.01
Experts	+	+	+	+	+	+	0	0	0		0.07
Stakeholders	0	0	+	+	0	0	0	0	0	0	

Note: Colored shading highlights increasing r^2 from yellow (0.050–0.099) to amber (0.100–0.249), orange (0.250–0.499), and red (≥0.500). *Reversibility* and *stakeholders* were power 3 and 4 transformed, respectively. Italics show parameters not used in the calculation of each index. *N* = negligible, i.e. <0.01.

four for H_E and three for H_{TRA} (Tables 2 and S10). However, relative mean covariance among indices and parameters varied little (H_{TRA}:24.6%; H_{CS}:24.1%; H_X:22.4%; H_E:21.3%). GLMs showed lower independent relationships between parameters and indices (Tables 2 and S11), with slight variations (H_E:8.0%; H_X:6.9%; H_{TRA}:5.9%; H_{CS}:5.6%). The H_{TRA} and H_{CS} indices correlated with expert opinion, while H_E and H_X correlated with severity, despite not being explicitly included. Reversibility was the weakest parameter, with no correlation to any index and least covariance (mean 4%; Table 2). Reversibility and proximity also explained very little independent deviance in the indices where they were explicitly included (H_{CS}:1.7% to H_{TRA}:2.2% and H_X:1.4% to H_{CS}:3.2%; Table S11).

HISP index parameters exhibited low inter-correlation (Tables 2 and S10). The VIF scores were mostly below 2.0, except for scope and proximity (2.08 and 2.10, respectively; Table S10). Indicators with high proximity to the conservation target showed high linkage and low scope, while those with high scope also showed high severity. Expert opinion correlated significantly with severity and scope and weakly with stakeholder opinion. The situation model and TRA parameters explained 36% of the variation in sociologists' opinion (mostly project scope), 24% for biologists (mostly severity), 14% for managers (mostly proximity), and 8% for stakeholders (mostly severity) (Table S12). Correlation between these different experts and other stakeholders was positive but highly variable and not significant ($r_s = 0.100–0.391$, $p = .009–.520$; $\alpha_{FDR} = 0.0056$; Table S13).

4 | DISCUSSION

4.1 | HISP effectiveness

The HISP approach successfully produced a diverse set of candidate indicators covering both ecological and socioeconomic dimensions and both proximate and ultimate threats. Ultimate drivers and socioeconomic indicators outnumbered direct threats and ecological indicators, helping to reduce common biases in conservation indicator selection and enabling concurrent use of ecological and socioeconomic measures to assess success (Ferraz et al., 2022). For example, the Magombera chameleon (*Kinyongia magomberae*), a flagship species at the case study site, was not among the top-ranked indicators—likely due to limited survey feasibility and ecological uncertainty—highlighting how HISP reduces bias towards charismatic species (Bakker et al., 2010; Hilty & Merenlender, 2000). Experts prioritized social, governance, and indirect threats, aligning with local priorities. All four HISP indices ranked above-ground biomass highly, affirming its central role in assessing forest productivity and function.

The HISP achieved parsimony through well-correlated indices, with all parameters contributing independently. The H_{E} index, though simpler and more opinion-based, showed similar correlations to more complex indices, making it the most parsimonious. However, its lower representation of socioeconomic indicators—such as forest legal status, wellbeing, patrols, and management training—suggests that expert opinion alone cannot fully capture situation model or TRA parameters. Likewise, H_{TRA} had only moderate correlation with H_{CS} (78%) and low correlation with H_{X} and H_{E}, indicating that ordinary threat ranking is also insufficient for capturing both expert opinions and situation model linkage.

Expert judgment is central to effective indicator selection. HISP supports and structures this input through a semi-systematic framework, in which expert and stakeholder rankings are combined with model-derived parameters—such as proximity to conservation targets and network centrality. These features provide a replicable scaffold to guide deliberation and help reveal patterns that may otherwise be overlooked, but they are not a substitute for practitioner insight. Final indicator choices are always interpreted through local knowledge and implementation realities—reinforcing that structured tools can enhance, not replace, expert-led decision-making (Salzer & Salafsky, 2006).

Although experts and stakeholder groups aligned broadly on category-level priorities, their individual indicator rankings diverged. As Game et al. (2018) showed, around 50% of expert-prioritized indicators were overlooked by stakeholders. This gap likely stems from differing perceptions: experts often emphasize biodiversity, while stakeholders focus on livelihoods (Engen et al., 2019). Sociologists aligned more closely with holistic conservation than biologists, though global surveys found that these differences may vary regionally, especially in low-income countries (Roe et al., 2013).

Model outcomes suggest scientific input can reflect major threats, while stakeholder input may represent unmeasured social or regional factors. This underscores the need for inclusive indicator selection to enhance evidence-based, context-specific decision-making within conservation practice (Bennett et al., 2017). While both expert and stakeholder rankings were suboptimal alone, their strong correlation with other HISP indices underscores their value, particularly in data-limited scenarios. Therefore, the HISP enables transparent incorporation of multiple viewpoints and identification of potential biases (Regan et al., 2004).

The H_{CS} index produced the most balanced and representative indicator set, showing the most parity with other HISP indices and their mean (Figure S3). By integrating TRA and situation model parameters, H_{CS} balanced ecological, socioeconomic, and governance indicators. H_{X}, closely correlated with H_{CS}, ranked second in index parity. For application beyond the case study site, we recommend combining insights from multiple HISP indices to better reflect the diverse goals of conservation projects.

4.2 | Choosing between HISP approaches

While further testing is needed, our case study suggests the H_{CS} index is the most widely applicable and among the most balanced and least biased, because it draws on parameters from situation modeling rather than relying solely on subjective input. It integrates expert knowledge within a structured framework, achieving strong index parity and parsimony, and thus emerges as our default recommendation—especially in contexts valuing both ecological and socioeconomic monitoring or where uncertainty is high. The H_{E} index, though more reliant on expert and stakeholder opinion, also reduced bias and correlated strongly with H_{X}. This suggests that H_{E} may be particularly useful where a project benefits from strong conservation expertise and local knowledge that it wishes to capitalize on, or where teams wish to demonstrate equitable input into the planning process. Furthermore, H_{X} may serve as a practical alternative in data-poor contexts where stakeholder input is limited or hard to source.

H_{TRA}, which prioritizes socioeconomic indicators, may be most appropriate in contexts with significant economic and wellbeing challenges, sensitive political situations, or high reliance on environmental resources. It centers on community-relevant indicators but assumes that project teams already understand local challenges. We underscore the importance of stakeholder participation in all cases, as community perspectives are essential for ensuring legitimacy and equity in conservation outcomes (Bennett et al., 2017).

4.3 | Method refinement and recommendations for practical application

HISP supports early-stage indicator prioritization based on conceptual structure, threat reduction logic, and socio-ecological relevance. Although the protocol does not formally incorporate results chains in its ranking process, knowledge of these causal pathways helped identify critical management intervention points during indicator identification (step 4). Results chains represent a project's theory of change by linking interventions to outcomes (Game et al., 2018; Margoluis et al., 2013). When derived from situation models, they can refine candidate indicators by aligning them with specific management strategies. While HISP excels at identifying indicators relevant to system-wide change, results chain logic offers a way to better identify indicators tied to specific actions and shorter-term outcomes. Together, these tools offer a two-tiered framework: situation models guide holistic indicator identification, while results chains refine indicator selection along intervention pathways. Future applications of HISP could enhance this integration by embedding results-chain structure directly into the ranking process.

Our case study identified 44 indicators, within the observed range of conservation practice. A review of 300 NGO initiatives (1993–2022) revealed projects used between 1 and 91 indicators (mean 15.2; SD = 11.7; Oliveira, unpublished). Although relatively high, this reflects an intentionally broad candidate set rather than a finalized monitoring plan. The HISP supports early-stage prioritization based on ecological relevance, threat linkages, and system representation, while feasibility considerations are addressed in subsequent steps (Figure 1). This sequencing ensures that strategically important indicators are not prematurely excluded due to temporary feasibility constraints. These later refinement steps—incorporating cost, stakeholder capacity, and implementation constraints—are currently being tested in follow-up HISP applications, including three additional conservation projects involving multidisciplinary practitioner teams (e.g., Oliveira et al., in prep.).

HISP is adaptable to different conservation scenarios. Weightings for parameters can be tailored to reflect donor, stakeholder, or government priorities. Indicators can also be adjusted retrospectively, based on evolving goals or data uncertainty. For example, to improve representation of social data, multiple community engagement methods could be incorporated. We also acknowledge that only one wellbeing indicator emerged from this study. Since human wellbeing is multidimensional and context-specific—especially in marginalized communities—our single wellbeing indicator was developed by our team as a complementary tool for measuring wellbeing (Loveridge et al., 2020). Thus, we acknowledge that the multidimensional components could be disaggregated to assess distinct dimensions such as material wellbeing, health, security, social wellbeing and freedom (Narayan et al., 2000).

Governance also emerged as a key ongoing challenge for conservation monitoring. Though only three governance indicators were prioritized, H_{TRA} and H_{CS} indices assigned them high weight, highlighting their potential role in future applications. Governance is often overlooked in conservation monitoring (Hausner et al., 2017), yet it has been strongly linked to both conservation success and human wellbeing globally (IPBES, 2019). This suggests that governance deserves greater emphasis in future adaptations of HISP.

Although this case study was selected to address traditional biases, broader trials are needed across varied conservation contexts. Projects in developed regions, which often face severe biodiversity loss despite stronger economies (Díaz et al., 2019), may benefit from HISP while requiring fewer socioeconomic indicators. Likewise, species-focused or multi-target initiatives may demand different balances of ecological and social indicators. The HISP approach is designed to adapt to these differences, supporting context-specific prioritization rather than enforcing uniform indicator sets. Although variation between conservation teams may introduce some bias, the HISP approach provides a structured process for identifying relevant factors and generating a comprehensive and logically ranked set of indicators.

5 | CONCLUSIONS

This paper validated the HISP as a novel tool for identifying and ranking indicators to evaluate conservation success. The HISP approach supports the identification of diverse indicators that encompass both ecological and socioeconomic factors, reducing traditional biases in conservation assessments. By employing expert and stakeholder input within a semi-systematic structure grounded in situation models, HISP reveals indicators that reflect system-wide priorities. Its alternative indices also allow teams to balance technical data, local knowledge, and stakeholder values. This makes HISP adaptable across different conservation contexts and levels of data availability. To strengthen causal attribution, future applications could more explicitly pair HISP with results-chain approaches to better align indicator rankings with specific conservation strategies. When integrated into strategic conservation planning—including subsequent cost and feasibility considerations—the HISP approach has the potential to enhance monitoring and management practices, helping to bridge the science–implementation gap.

AUTHOR CONTRIBUTIONS

Andrew Marshall: conceptualization, funding acquisition, methodology, investigation, formal analysis, data curation, writing – original draft, review & editing, supervision. **Rodrigo M. de Oliveira:** writing – original draft, review & editing. **Ricardo L. de Figueiredo:** writing – original draft, formal analysis. **John Meadows, Frederick Sutton, Hayley Blackwell, Jennifer Archer:** writing – review & editing. **Charles Meshack, Fadhili M. Njilima, Susannah M. Sallu:** validation, writing – review & editing.

ACKNOWLEDGMENTS

We are grateful to Nancy L. Barrickman for her input to all human elements of the strategic planning and hands-on participation in village visits and indicator scoring. Thanks also to Neil D. Burgess for his involvement in the scoring process. We thank our various public and private donors, particularly Flamingo Land. We thank the Tanzania Wildlife Research Institute and Tanzania Commission for Science and Technology for research permits. Open access publishing facilitated by University of the Sunshine Coast, as part of the Wiley - University of the Sunshine Coast agreement via the Council of Australasian University Librarians.

CONFLICT OF INTEREST STATEMENT

The authors declare that they have no known competing financial interests or personal relationships that could appear to influence the work reported in this paper.

FUNDING INFORMATION

Andrew R. Marshall was funded by an Australian Research Council Future Fellowship FT170100279. Rodrigo M. de Oliveira was supported by an Australian Government Research Training Program Scholarship and Noosa Biosphere Reserve Foundation Scholarship.

DATA AVAILABILITY STATEMENT

Data will be made available on request.

ETHICS STATEMENT

This research received ethical review and approval from the Flamingo Land Ethics Committee.

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How to cite this article: Marshall, A. R., de Oliveira, R. M., de Figueiredo, R. L., Meadows, J., Sutton, F., Blackwell, H., Archer, J., Meshack, C., Njilima, F. M., & Salluh, S. M. (2026). Evaluating a strategic approach for identifying and ranking holistic sets of indicators of conservation project success. *Conservation Science and Practice*, e70351. https://doi.org/10.1111/csp2.70351