Catalyzing Success in Community-based Conservation

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Abstract

Efforts to devolve rights and engage Indigenous Peoples and local communities in conservation have increased the demand for evidence of the efficacy of community-based conservation (CBC) and insights into what enables its success. We curated a diverse sample of 128 projects reporting both human well-being and environmental outcomes and coded 57 national-level, community-level, project-level, and control variables. We found that over 80% of CBC projects had some positive human well-being or environmental outcomes, but only 32% achieved positive outcomes for both. Applying Random Forest Classification, we found that the best predictors of combined success could be distilled to 17 variables representative of various policy levers and actionable opportunities for conservation practitioners related to national contexts, community characteristics, and the implementation of various strategies and interventions informed by existing CBC frameworks. We found that CBC projects had higher probabilities of combined success when they occurred in national contexts supportive of effective local governance, partnered with socially cohesive communities inclined toward collective action, acknowledged conflict or trust issues that could undermine it, promoted economic diversification, and invested in various capacity-building interventions, providing important insights into how to encourage greater success in CBC.

1. Introduction

Interest in community-based conservation (CBC) has grown concurrent with the recognition of its potential to advance conservation goals while strengthening the agency and well-being of Indigenous Peoples and local communities (IPLCs). IPLCs govern more than a quarter of the world's terrestrial area distributed across 75% of the world's ecoregions (Rights and Resources Initiative 2015; Garnett et al. 2018; Corrigan et al. 2021). These landscapes have immense socio-cultural and economic value to the communities connected to them (Bridgewater & Rotherham 2019), as well as exceptional conservation value to the world beyond (Frechette et al. 2018; Schuster et al. 2019; Fa et al. 2020; Walker et al. 2020). The diverse values embodied by IPLC landscapes are currently under immense pressure from globalization and extractive industrial development (Gilberthorpe & Hilson 2014; IPBES 2019; Kennedy et al. 2022), intersecting local and supra-local interests (Dinerstein et al. 2019), and forcing acknowledgement of a legacy of ineffective conservation policies and approaches (Brockington & Igoe 2006; Zimmerer 2006; Dowie 2009; IUCN 2020; Tauli-Corpus et al. 2020).

For normative and practical reasons, it is widely accepted that protection of such places should be achieved with a community-based approach (Ellis & Mahrabi 2019; Waldron et al. 2020), which necessitates further evaluation of CBC frameworks that guide how conservation practitioners engage with IPLCs. Despite long-standing calls for adopting a community-based approach (e.g., Chapin 2004), practitioner frameworks and guidance for effectively doing so are still evolving. CBC frameworks now exist across multiple conservation organizations (e.g., Ostrom et al. 2009; TNC 2017; Mahajan et al. 2021) and generally coalesce around strategies and interventions that create the enabling conditions for IPLCs to effectively govern and continue stewarding their land and resources (Ostrom 1990; Adams & Hulme 2001). These enabling conditions are supported by many broadly conceived strategies and interventions well known to CBC practitioners, including those that help secure their rights to territory and resources (Robinson et al. 2017; Tseng et al. 2021), strengthen local leadership and governance capacity (Moore et al. 2006; Brooks et al. 2013), create forums for multistakeholder engagement and decision-making (Edmunds & Wollenberg 2002; Kusters et al. 2018), and provide sustainable economic development opportunities (Livelihoods and Governance Programme 2013; Roe et al. 2013, 2015).

Although these elements are often researched independently, CBC is context-dependent and multifaceted (Schwartz et al. 2018; Mahajan et al. 2021). Recent reviews of CBC projects suggest that successes are possible under certain conditions and with certain interventions; however, many are largely descriptive (e.g., Burivalova et al. 2017, 2019) or based on conventional statistical analyses (bivariate or multivariate) of CBC outcomes and their explanatory variables (Brooks et al. 2013; Brooks 2017; D'Armengol et al. 2018; Hajjar et al. 2021). Furthermore, some of these reviews focus on single dimension outcomes (e.g., Roe et al. 2015), making it difficult to examine the relative importance of the diverse strategies and interventions commonly leveraged in a single project, the necessity for CBC to generate benefits for nature without harm to people, and the frequency with which they succeed at generating benefits for both. This combined outcome is of particular interest, as dual benefits are often an explicit goal of CBC, though notoriously difficult to achieve (Chhatre & Agrawal 2009; McShane et al. 2011; Brooks 2017). As a result, further synthesis of the evidence is needed to assess the efficacy of commonly employed strategies and interventions, as well as to ensure better outcomes for future conservation efforts (Sutherland et al. 2004; Pullin & Knight 2009).

We addressed this need with a sample of 128 CBC projects reporting on both human well-being and environmental outcomes and coded 65 different variables overall informed by existing CBC frameworks (e.g., TNC 2017; Mahajan et al. 2021). We then employed a machine learning method to identify those that best predicted combined success. This approach overcomes the drawbacks of previous approaches in that it requires little to no *a priori* knowledge about the relative importance of different explanatory variables, can appropriately model correlated variables and nonlinear relationships common with socioecological data, and can better detect small individual effects. As a result, our analysis provides novel insights into what might catalyze CBC success, which can be used to inform the development of more effective strategies and interventions and to identify evidence gaps that must be filled to strengthen the evidentiary backing of existing CBC frameworks.

2. Methods

Our approach involved 1) curation, coding, and processing of a sample of CBC projects; 2) statistical summaries of indicator and project-level social, economic, and environmental outcomes; 3) Random Forest Classification (RFC) of national, community, and project-level variables to identify those important to combined success; and 4) estimation of accumulated local effects (ALE) to describe how each effects the probability of achieving it. Data compilation and management were performed in Excel (Excel for MSO 365, version 1908), and analyses and mapping were performed using the statistical computing platform R (R Core Team, 2019, version 4.0.3) and ArcMap (version 10.6.1), respectively.

2.1 Curation, coding, and processing of the sample

To create our sample, we considered studies in English with relevant titles and abstracts, where full texts were accessible that offered adequate descriptions of community-level characteristics, interventions, and outcomes where both human well-being *and* environmental outcomes were reported (see Table S1). Previous reviews of CBC have noted a paucity of information on outcomes and enabling conditions, as well as a high level of variability in the quality of the evidence reported (Pullin & Stewart 2006). As a result, we allowed diverse sources of evidence from peer-review journals, books, theses, dissertations, conference proceedings and technical reports. We also permitted diverse types of evidence generated from methodological approaches ranging from case studies to quasi-experimental research designs. We included projects that reported qualitative and

quantitative indicators, as well as those with and without controls in time, treatment, or consideration for confounding variables. Because we permitted such diverse evidence, we also calculated composite measures of majority indicator type and design for each project and used these to proxy for the strength and quality of the evidence reported (see Figure S1, Table S2).

To curate this sample, we first considered the projects vetted in previous reviews of CBC that were broad in scope or had an apparent connection to the strategies and interventions suggested by existing CBC frameworks we were specifically interested in testing (TNC 2017; Mahajan et al. 2021). Though not exhaustive, this included two reviews of CBC and ICDPs (Brooks et al. 2006, 2013); a specific review of alternative livelihood strategies (Roe et al. 2015); and a review of key CBC strategies implemented in tropical forest conservation, including protected areas, community-based natural resource management, certification, and payments for ecosystem services (Burivalova et al. 2019). We expanded this sample by conducting a supplementary literature search in February 2020 focused on filling gaps in the date ranges and CBC strategies captured by these previous reviews. We employed best practices in designing our search strategy and selection process (Petrokofsky 2018), implemented the search in Google Scholar, and exported search returns using Publish or Perish software (Harzing 2007). Similar to Brooks et al. (2006, 2013), we searched for "community-based conservation" or "CBC" or "integrated conservation and development" or "ICDP" and “~impact and ~ environment” and restricted the dates to 2012–2020 to capture publications that minimized the possibility for duplicates, which were manually removed when they occurred.

We then read each paper and coded their social, economic, and environmental outcomes (intended and unintended). This coding included an outcome and indicator category (e.g., environmental outcome: restoration and recovery indicator), description (e.g., forest cover), valence (e.g., increasing), type (e.g., quantitative), design (e.g., time series) and outcome (e.g., positive). Indicator outcomes were based on an interpretation of the indicator’s trend and impact, which we coded as “negative,” “neutral” or “positive”. Project-level social, economic, and environmental outcomes were assigned by aggregation of all the individual indicators measured (statistically significant or not) and were scored as “negative” if all indicators were negative, negative and neutral, or neutral only; “mixed” if there were some positive indicators; and “positive” if all indicators were positive. Last, we used project-level outcomes to develop the response variable of our RFC model, “combined success”, where “success” was assigned to projects if all the human well-being (social and/or economic) and environmental outcomes measured were “positive” and a “failure” if otherwise. An analysis of the sensitivity of our results to response variable coding is presented in the supplement (see Figure S7).

To better understand the factors associated with success at generating benefits for people and nature, we coded or obtained from supplementary sources a total of 57 explanatory variables with hypothesized importance to project outcomes, including seven variables related to national context, 17 community characteristics, 27 attributes of project design and implementation and 6 control variables (Table S2). Before starting, we developed a coding scheme from the examples of previous reviews, and where there was overlap in variables of interest (e.g., population size, heterogeneity), we attempted to retain the same categorical levels. Our coding process was adaptive. We developed and tested our coding scheme on a small sample of studies and refined it through feedback and discussion among coders to clarify coding challenges.

Missing data are commonly cited with the CBC literature as a function of inadequate monitoring and evaluation or an incomplete reporting of the numerous factors that may be relevant to project outcomes (Humphries et al.

2018). Most explanatory variables we coded had some proportion of missing data (36 out of 57, 63%). Of these, 20 had missing data proportions (NDP > 0.30), which we define as an “evidence gap” and preclude from imputation and subsequent modeling (Table S4). Similar to other systematic reviews and analyses of conservation outcomes (Brooks et al. 2013; Hajjar et al. 2021), we imputed missing values for explanatory variables with NDP ≤ 0.30. Overall, missingness was negligible, ranging from 0–16% among our explanatory variables, and sensitivity analyses revealed no evidence of a positive correlation between a variable’s degree of missingness or subsequent imputation and its importance (Figure S6). We used the R package *missForest* (Stekhoven 2013), a nonparametric imputation method combining random forest and predictive mean matching, to fill missing values in each explanatory variable by considering all other information available for the project. This process resulted in an imputation error (IE) statistic for each explanatory variable, normalized mean squared error (NMSE) for numerical variables or proportion falsely classified (PFC) for categorical variables. We used IE ≤ 0.30 as our threshold for variable processing, which resulted in the exclusion of three control variables (Table S4).

Last, we performed a second blind review of a stratified random sample of 20% of our inclusion set to calculate a statistic of interrater reliability (IRR) for each coded variable (Collaboration for Environmental Evidence 2013). We used the R package *IRR* (Garner et al. 2019) to calculate Cohen’s Kappa, which represents a level of agreement across all coders beyond what might be expected by chance (Cohen 1960). An IRR < 0.60 suggests less than moderate agreement (McHugh 2012), which affected six of our original explanatory variables (Table S4). Collectively, these statistics were used to process the data obtained from the sample. Explanatory variables with NDP ≤ 0.30, IE ≤ 0.30, and IRR ≥ 0.60 met our criteria for modeling, including 28 variables overall (Table S4).

2.2 Descriptive summaries of projects and outcomes

We summarized the indicator and project-level outcomes of our project sample (n = 128) using the R packages *ggplot2* (Wickham 2016) and *likert* (Bryer & Speerschneider 2016).

2.3 Random Forest Classification

We then employed RFC (Breiman 2001) to identify the variables most important to combined success in human well-being (social and/or economic) and environmental outcomes. RFC is a specific implementation of a well-established decision-tree method known as Classification and Regression Tree (CART) analysis (WeiYin 2008; Humphries et al. 2018). It provides a flexible, nonparametric approach to exploring the effects of numerous theoretically important explanatory variables on CBC project outcomes. A key advantage of RFC as a tool for data exploration and prediction is its ease of implementation and robustness to challenges common to the socioecological data typically available for CBC projects (Cutler et al. 2007) and to the current state of our knowledge about the numerous factors that might influence their ability to achieve benefits for both people and nature.

2.4 Elements of the model

Our response variable (target) for the RFC model was “combined success,” while the variables (features) of the model were drawn from the 57 explanatory and control variables informed by previous reviews and existing CBC frameworks (Table S2). A total of 28 explanatory variables met our criteria for consideration in the model (NDP ≤ 0.30, IE ≤ 0.30 and IRR ≥ 0.60) (Table S4).

2.5 Modeling combined success

Prior to modeling, our project sample (n = 128) was parsed into training and test data. The latter we established from a randomly selected 20% of the original sample (n = 26). These test data were balanced in their representation of project outcomes (0:1 = 13:13). We used the remaining 80% of the sample to train the RFC model (n = 102, 0:1 = 74:28). The performance of various machine learning methods is sensitive to this initial split. We provide an analysis of the sensitivity of our results to different training and test assignments in Figure S5. In addition, RFC is adversely affected by unbalanced training data (Shaikhina et al. 2019). Balancing can significantly improve the performance of RFC, which effectively works by under-sampling the majority class (i.e., failures) and over-sampling the minority class (i.e., successes). In Table S5, we provide a comparison of model performance measures between the original, unbalanced training dataset and a number of different balanced training datasets achieved by the synthetic matching algorithm SMOTE (Chawla et al. 2002) from the R package *DMwR* (Torgo 2010). The balanced training dataset, train (c), had the best model performance and is the one we feature in our analysis.

We ran bootstrapped ($\mathbf{B}$ = 1000) RFC models on this training dataset using the R package *randomForest* (Liaw & Wiener 2002; Paluszynska et al. 2019) and optimized model parameters using grid search (Reif et al. 2012). In total, 28 variables met our criteria for consideration (NDP $\leq$ 0.30, IE $\leq$ 0.30, IRR $\geq$ 0.60). An iterative variable selection process aimed at improving model performance reduced this set to 17 variables through the following steps: 1) pruning of redundant variables via selection of a representative from within the suite based on feature importance scores and accumulated local effects (ALES); 2) stepwise tests of removing variables with ALES that appeared uninformative or lacked theoretical justification; and 3) removal of remaining variables with feature importance scores $\leq$ 0.50 Mean Decrease Gini.

2.6 Model performance and prediction

We report several measures of performance for the resulting RFC model, including accuracy, recall, and precision, to assess 1) the proportion of all cases correctly predicted by the model; 2) the proportion of actual successes correctly predicted to identify omission errors; and 3) the proportion of predicted successes that were actually successes to identify commission errors (Frank 2019). We also used the R packages, *ROCR* and *AUC* (Sing et al. 2005; Ballings & Van den Poel 2013) to derive receiver operating characteristic (ROC) and area under the curve (AUC) statistics to illustrate the diagnostic ability of the model as a binary classifier. We bootstrap estimated ($\mathbf{B}$ = 1000) each of these measures to assess the model's fit to the sample of CBC projects it was built on (Figure S3a), as well as its performance on test data (Figure S3b). We accept ROC-AUC $\geq$ 0.70 on test data holdout as a suitable level of discrimination between CBC outcomes and a minimum value of model performance to evaluate the model's utility for predicting combined success. Across the variable and model selection process described above, ROC-AUC on test data holdout was improved from 0.58 (0.47, 0.67) to 0.70 (0.60, 0.79).

2.7 Estimating variable effects

Interpretation of a variable's effects on the probability of combined success requires coupling with additional analytical methods (Molnar 2019). We used the R packages *iml* (Molnar et al. 2018) and *ALEplot* (Apley 2018) to calculate bootstrap estimated ($\mathbf{B}$ = 1000) accumulated local effects (ALE) for each variable in the RFC model. Similar to partial dependance plots (PDPs) and individual conditional expectation (ICE) plots, ALE plots illustrate a variable's overall effect on the predicted outcome. We relied on ALE plots to visualize the effects of individual

features on the probability of combined success given that they are less computationally demanding, capable of dealing with moderately correlated variables, and amenable to exploring interactions (Apley & Zhu 2020). Last, we report percentile-based 90% confidence intervals (CIs) for our bootstrapped estimates given the smaller sample size on which the model was trained and present overall and two-way interactions between the variables of the model in the supplement (see Figure S8).

3. Results

3.1 Description of the sample

Our sample included 128 CBC projects implemented across 37 different countries in Latin America, Africa, and Asia, spanning terrestrial (74%), marine/coastal (19%), and freshwater (7%) ecosystems (Fig. 1, Table S7). Twelve countries had one project represented in the sample, while Cameroon, India, Mexico, Indonesia, Brazil, and Tanzania had multiple projects. Most projects were from peer-review journals (79%) and were implemented by government agencies (42%), NGOs (13%), or partnerships between the two (38%). Most projects (67%) were also at a later stage of implementation (6 + years) at the time of their evaluation. Projects were evaluated between 1983 and 2017, with 80% occurring prior to 2010; most of those between 2000 and 2004. With regard to the types of evidence reported, 38% of projects reported quantitative indicators as the majority, 34% qualitative, 26% author-reported or secondary sources, and 2% had a mix of indicator types with no clear majority. While 49% of projects reported indicators with treatment or time controls as the majority, 43% with no control, and 8% reported indicators with mixed methodological designs and no clear majority. Of the projects that reported indicator outcomes against a control in treatment or time, nearly half considered additional confounding variables, and 17% employed more rigorous designs (e.g., quasi-experimental or randomized control trials). Collectively, these statistics suggest that most of the evidence in our sample was derived from primary data collection (72%), using methodological designs considerate of at least one or more controlling variables (58%). See the supplementary information for a general description of the sample (Figure S1).

3.2 CBC outcomes

Across social, economic, and environmental outcomes, we found that positive indicators were frequently reported in at least one domain, but there was variation within and trade-offs among them. Of the 110 projects reporting social outcomes, 42% reported all positive indicators, and an additional 48% reported mixed results (Fig. 2a, S2a). There was notable variation across social indicator categories. For example, indicators related to health, education, and quality of life were predominately positive (73%), followed by indicators related to attitudes and behaviors impacting natural resource management (e.g., willingness to adopt new or improved practices) (68%) and conservation awareness and attitudes (67%). In contrast, the majority (58–59%) of indicators related to access and use, equity and representativeness, and well-being and empowerment were more often neutral to negative. Table S3 provides descriptions and sample sizes of indicator categories.

Of the 113 projects that reported economic outcomes, 50% had all positive indicators, and an additional 35% were mixed (Fig. 2b, S2b). We observed less variation within economic indicator categories, as most had a majority that were positive. Enterprise establishment indicators had the highest proportion of positive outcomes (91%), followed by indicators related to efficiency, productivity, and sustainability (85%). However, improvements in poverty metrics and perceptions of economic security that would ideally follow the establishment of a new

livelihood enterprise (e.g., ecotourism) occurred less often. We observed this specifically with improvements in employment opportunity, income, livelihoods and living standards. While a slight majority of indicators in these categories were positive, each had a considerable proportion of neutral to negative reporting (range: 37–40%).

For environmental outcomes, 60% reported all positive indicators, and an additional 20% were mixed (Fig. 2c, S2c). Similar to the economic indicator categories above, all environmental subcategories tended to be positive. Indicators related to restoration and recovery, diversity and resilience, and pro-conservation activities (e.g., patrolling, nest protection, etc.) were predominately positive (> 75%). Meanwhile, indicators related to abundance and extent, ecological condition and function, disturbance, degradation, and illegal activity had higher neutral to negative reporting (range: 32–42%).

It is widely acknowledged that achieving success in both human well-being and environmental outcomes can be difficult and that trade-offs are common (Chhatre & Agrawal 2009; McShane et al. 2011; Roe et al. 2013; Hajjar et al. 2021). Consistent with this, we observed combined success with less frequency. Of the 128 projects that reported a combination of human well-being (social and/or economic) and environmental indicators, 32% achieved positive outcomes in all the domains they measured (Fig. 2d, S2d). The results of the RFC model were used to identify the predictors of this outcome.

3.3 Importance of national, community, and project-level variables to CBC outcomes

Our RFC model of combined success is conditioned on 17 explanatory variables retained through variable processing and selection (Table 1, Table S4). Bootstrap estimated ($\mathbf{B}$ = 1000) feature importance scores are shown in Fig. 3 (Table S6). Of note is that the control variable project period ranked highest in importance, although national-level variables creating favorable enabling conditions for effective local governance were among the most important (environmental democracy ranked #2, political stability ranked #3, voice and accountability ranked #4, and IPLC legal insecurity ranked #5). Meanwhile, project-level variables made up the greatest share of the variables important to combined success (53%, n = 9:17). Two community-level variables also met our feature importance threshold (Mean Decrease Gini ≥ 0.50), though they ranked relatively lower than others (economy ranked #12 and social cohesion challenge ranked #17). Model performance statistics on training data confirmed that these 17 explanatory variables were good at discerning the outcomes reported in the project sample (ROC-AUC = 0.97; 0.95, 0.99), while model performance on test data holdout suggested that they are reasonably good at discerning the outcomes of projects beyond the sample as well (ROC-AUC = 0.70; 0.60, 0.79) (Figure S3).

Table 1
Definitions and descriptive statistics of the variables used in the RFC model.

RESPONSE VARIABLE (TARGET)					Obs.		
					Train	Train(c)	Test
Outcome	**Combined success**: Project-level outcome calculated from the combination of human wellbeing (social and/or economic) and environmental outcomes reported. Coded as: (1) "success" if all single dimension outcomes were positive and (0) "failure" if otherwise.				102	112	26
	0) Failure				74	56	13
	1) Success				28	56	13
CONTINUOUS EXPLANATORY VARIABLES (FEATURES)[1]			Min	Mean	Max	SE	
National-level (n = 4)	**Environmental democracy (+)**: Index score for environmental democracy based on indicators of the extent to which a country's citizens enjoy access to information, participation in decision-making forums, and justice in environmental matters (e.g., laws and regulations governing freedom-of-information; regulation on extractive industry, requirement for consultation, etc.). Values were obtained from World Resources Institute Environmental Democracy Index (Worker & De Silva 2015). Higher values indicate greater environmental democracy. Since this index was compiled in 2017, we acknowledge the possibility that it may overestimate levels of environmental democracy for earlier projects.	**Train**:	0.09	1.34	1.90	0.04	
		Train(c):	0.09	1.31	1.90	0.03	
		Test:	0.90	1.36	2.14	0.10	
	IPLC Legal Insecurity (-): Index score of the legal security IPLCs have over their territories and resources as assessed from numerous indicators. Values for each country were obtained by taking the least secure score from LandMark's separate IP and LC Legal Security Indices. Higher values indicate greater insecurity Landmark (Wily et al. 2018). Since this index was compiled in 2019, we acknowledge the possibility that it may overestimate levels of legal security for earlier projects.	**Train**:	1.10	2.20	4.00	0.08	
		Train(c):	1.10	2.22	4.00	0.08	
		Test:	1.10	2.15	4.00	0.15	
	Political Stability (+): Index score for political stability based on indicators of the likelihood of political instability and/or politically motivated violence (e.g., civil unrest, armed conflict, ethnic tensions). Values were obtained from the World Bank Political Stability Index for the year of project assessment, or next closest within a 2-year window (Kaufmann et al. 2010). Higher values indicate greater political stability.	**Train**:	-1.95	-0.44	1.01	0.07	
		Train(c):	-1.79	-0.58	0.89	0.06	

[1] The hypothesized effect for each explanatory variable follows its name in parentheses (see Table S2 for more details).

RESPONSE VARIABLE (TARGET)				Obs.		
				Train	Train(c)	Test
		Test:	-1.87	-0.48	1.14	0.14
	Voice and Accountability (+): Index score for voice and accountability based on indicators of the extent to which individuals can participate and be adequately represented in political processes (e.g., perceptions of confidence in electoral processes, freedom of expression, the accountability of public officials). Values were obtained from the World Bank Voice and Accountability Index for the year of project assessment (or next closest within a 2-year window) (Kaufmann et al. 2010). Higher values indicate greater voice and accountability.	**Train**:	-1.58	-0.11	1.13	0.06
		Train(c):	-1.40	-0.15	1.13	0.05
		Test:	-1.63	-0.11	1.29	0.12

CATEGORICAL EXPLANATORY VARIABLES (FEATURES)		Obs.		
		Train	Train(c)	Test
Community-level (n = 2)	**Economy (+)**: Predominant type of economy that best characterizes the community. Coded as: (1); subsistence-based; (2) mixed; or (3) market-based. Note that ordinal scale reflects increasing levels of market access.			
	1) Subsistence-based	46	51	11
	2) Mixed	53	58	12
	3) Market-based	3	3	3
	Social cohesion challenge (-): Indications of a potential social cohesion challenge referenced directly or suggested by demographic information related to population size, diversity, or pressure. Coded as: (0) no; or (1) yes.			
	0) No	34	36	15
	1) Yes	68	76	11
Project-level (n = 9)	**Acknowledged conflict or trust issues (+)**: Whether conflict or trust issues in the community were acknowledged and attempts to address via various means (e.g., conflict resolution, trust or network-building) were suggested. Coded as: (0) no; or (1) yes.			
	0) No	63	75	14

[1] The hypothesized effect for each explanatory variable follows its name in parentheses (see Table S2 for more details).

RESPONSE VARIABLE (TARGET)	Obs.		
	Train	Train(c)	Test
1) Yes	39	37	12
Conservation biome (x): The predominant biome in which the project occurs. Coded as: terrestrial; freshwater; or marine/coastal.			
1) Terrestrial	78	82	17
2) Freshwater	6	4	2
3) Marine/Coastal	18	26	7
Conservation target (x): The primary conservation target of the project. Coded as: targeted species and habitats; biodiversity and landscapes; or ecosystem health and services.			
1) Targeted species and habitats	17	25	9
2) Biodiversity and landscapes	75	77	16
3) Ecosystem health or services	10	10	1
Economic development intervention type (+/x): Type of economic development intervention implemented by the project. Coded as: none or assumed benefits; commercial permits and concessions (e.g., leases); compensation-focused (e.g., payment for conservation activities like patrolling, or provision of ecosystem services, etc.); or diversification-focused (e.g., introduction of alternative methods, resources, or occupations; small business loans and incentives for alternative livelihoods development).			
1) None or assumed benefits	22	29	5
2) Commercial permits and concessions	11	15	4
3) Compensation-focused	28	22	6
4) Diversification-focused	41	46	11
Health or infrastructure intervention (+): Whether there was a healthcare or infrastructure component to the project (e.g., nutritional programs, vaccination clinics, roads, schools, wells, irrigation networks). Coded as: (0) no; or (1) yes.			
0) No	26	39	14
1) Yes	76	73	12

[1] The hypothesized effect for each explanatory variable follows its name in parentheses (see Table S2 for more details).

RESPONSE VARIABLE (TARGET)		Obs.		
		Train	Train(c)	Test
	Leadership or governance intervention (+): Whether there was a human, social or institutional capacity building component to the project focused on strengthening community leadership or the capacity for natural resource governance (e.g., knowledge exchange, training in conflict resolution, establishment of CBOs, land use planning, etc.). Coded as: (0) no; or (1) yes.			
	0) No	37	51	14
	1) Yes	65	61	12
	Multistakeholder intervention (+): Whether there was an explicit multistakeholder intervention implemented in the project (e.g., coordination of stakeholders, vertical integration of nested institutions of governance, political representation in decision-making forums). Coded as: (0) no; or (1) yes.			
	0) No	71	81	24
	1) Yes	31	31	2
	Tenure security component (+): Whether the community had secure tenure at the time of intervention (as suggested by property type) or there was an effort to increase it as part of project design (e.g., formalization, titling).			
	0) No	56	72	14
	1) Yes	46	40	12
	Training or technical assistance intervention (+): Whether there was a human capacity building component to the project focused on the provision of training or technical assistance. Coded as: (0) no; or (1) yes.			
	0) No	35	45	16
	1) Yes	67	67	10
Control (n = 2)	**Implementation stage (+)**: How old the project was, or the implementation stage of the project at the time of its evaluation. Coded as: (1) early (0–2 years); (2) intermediate (3–5 years); or (3) late (6 + years). Note that scale reflects increasing project duration and maturity.			
	1) Early 0–2 years	7	14	3
	2) Intermediate 3–5 years	24	23	8
	3) Late 6 + years	71	75	15
	Project period (x): The time period in which the project was assessed. Coded as: (1) pre-2010, or (2) 2010+.			

[1] The hypothesized effect for each explanatory variable follows its name in parentheses (see Table S2 for more details).

RESPONSE VARIABLE (TARGET)	Obs.		
	Train	Train(c)	Test
1) Pre-2010	81	85	21
2) 2010+	21	27	5

[1] The hypothesized effect for each explanatory variable follows its name in parentheses (see Table S2 for more details).

3.4 Effects of important variables on CBC outcomes

Bootstrap estimated ($\mathbf{B}$ = 1000) accumulated local effects for each of these 17 variables are shown in Fig. 4. Most variables showed trends consistent with their hypothesized effect (see Table 1). For example, the national-level variables environmental democracy, political stability, and voice and accountability showed significant effects across their range, though IPLC legal insecurity showed no detectable pattern despite being important to overall model performance (Fig. 4a). Of note is that we observed significant negative effects from the least favorable national contexts associated with environmental democracy, political stability, and voice and accountability. While projects occurring in countries with the highest environmental democracy had significant positive effects (12%, LL: 6%, UL: 17%).

Consistent with their relatively lower feature importance, we found that community characteristics were less influential (Fig. 4b). For example, we observed no evidence of an effect with respect to economy type and level of market integration, while a potential negative effect was suggested for social cohesion challenge, as indicated by a range of negative estimates bounded by 0 (-1%, LL: -2%, UL: 0).

Meanwhile, many aspects of project design and implementation influenced CBC outcomes (Fig. 4c). Economic development interventions, particularly diversification-focused strategies such as alternative methods, resources, or occupations, had a significant positive effect (4%, LL: 1%, UL: 7%). Whereas projects based on commercial permits and concessions (e.g., timber leases) showed a significant negative effect (-7%, LL: -12%, UL: -3%). We observed no evidence of an effect for compensation-focused strategies such as Payment for Ecosystem Services (PES).

Training or technical assistance interventions followed in importance, and their implementation had a significant positive effect (3%, LL: 1%, UL: 5%). Following that, acknowledged conflict or trust issues, indicated by various trust-building, networking, and conflict resolution activities, had a significant positive effect (5%, LL: 2%, UL: 9%). Additional capacity-building interventions showed potential positive effects, including leadership or governance interventions (2%, LL: 0%, UL: 4%) and health or infrastructure interventions (1%, LL: 0%, UL: 3%). We observed no evidence of an effect for conservation biome, conservation target, tenure security component (e.g., implementation in communities with existing forms of tenure suggestive of increased security such as private or common property or efforts to increase tenure security through interventions such as formalization and titling) or multistakeholder interventions (e.g., vertical integration of nested institutions of governance, forums to improve local participation in political processes and decision-making bodies).

Last, we observed notable effects for two control variables, project period and implementation stage (Fig. 4d). With regard to the project period, post-2010 projects had a significant positive effect (16%, LL: 13%, UL: 20%).

While the plot for the implementation stage variable showed that very young projects had a potential negative effect (-4%, LL: -9%, UL: 0%), and late-state projects of 6 + years had a potential positive effect (1%, LL: 0%, UL: 2%).

4. Discussion

We provide a comprehensive overview of the catalysts of success in CBC using a framework-informed, exploratory analytical approach that is well suited to learning from the small samples and highly dimensional, often correlated data common to CBC literature. We find that external factors and enabling conditions have a considerable influence on place-based outcomes and, to a lesser degree, certain characteristics of the communities themselves. We also find that many of the project-level interventions at the discretion of conservation practitioners do, in fact, have a positive effect on human well-being and environmental outcomes. Our findings offer key insights into what pushes the needle toward greater CBC effectiveness in delivering benefits for people and nature, provide evidentiary support for existing CBC frameworks (e.g., TNC 2017; Mahajan et al. 2021), and clarify evidence gaps requiring further study.

4.1 National contexts supportive of effective local governance affect CBC outcomes

The importance of the context in which CBC is embedded is a widely held though frequently untested assumption (Dickman et al. 2015; Miller et al. 2015). In our study, we considered several national-level variables with hypothesized relevance to CBC outcomes and found three to have significant effects, including environmental democracy, political stability, and voice and accountability. In contrast to previous reviews that aggregate several national-level variables into a single dimension and have found none or negative effects (Brooks et al. 2013; Hajjar et al. 2021), we tested the effects of each independently and found different results. We suggest that each national-level indicator represents a different aspect of the social, economic, and political context influencing the operational environment and the capacity for community governance and stewardship. Particularly important to the combined success of CBC projects were national contexts that 1) support free prior and informed consent and provide pathways for communities to seek justice in environmental matters; 2) provide communities access to information and the ability to participate and freely express their interests in political and decision-making processes (Barelli 2012; Tomlinson 2019); and 3) promote stability with respect to supra-local governance structures, regulatory environments, recognition, and enforcement of rights (Ribot et al. 2006). Consideration of these readily available national indicators provides important situational awareness for conservation practitioners with bearing on feasibility and conservation investment prioritization (e.g., Eklund et al. 2011; Garnett et al. 2011), as well as indicating which strategies might be leveraged in response. We argue that keeping these indicators disaggregated makes them more accessible and makes the interpretation of potential solutions and recommended actions more straightforward. For example, greater investment in capacity-building efforts that foster community engagement and representation in decision-making processes might be suggested where environmental democracy and voice and accountability are low. Local efforts might involve creating or strengthening community-based organizations and building the capacity for community leaders to more readily participate in decision-making fora, while supra-local efforts might involve advocacy for the enforcement of existing frameworks that call for equity and the inclusion of marginalized groups, increasing

their transparency and accountability and removing barriers to access and participation (Gaventa & McGee 2013; Kennedy et al. 2022).

4.2 Social cohesion and trust affect CBC outcomes

Social cohesion and collective action are prerequisites for effective natural resource governance, which is foundational to many CBC frameworks (Olson 1965; Agrawal & Ostrom 2001; Colfer 2007; Bodin 2017; Mahajan et al. 2021). There is a substantial body of literature that discusses the importance of social cohesion to collective action and governance, which in turn is influenced by several community characteristics. Low levels of social cohesion are expected when communities lack familiarity, frequent interaction, shared identity and purpose, reciprocity and trust (Olson 1965; Ostrom 1990, 2010). It is reasonable to assume that these disabling conditions are more likely to exist in communities that are large, diverse, rapidly changing, involved in conflict, have pronounced inequality, or have experienced legacies of marginalization and dispossession (Stern & Coleman 2015; Manfredo et al. 2017). Such conditions are not uncommon in the communities where CBC occurs.

We found that social cohesion challenges had a potential negative effect on CBC outcomes, whereas acknowledgement of conflict or trust issues (an important foundational element for social cohesion) and indications that projects made attempts to address them had a significant positive effect. Collectively, these findings suggest that increased attention to the cohesiveness of the community and investments in innovative strategies that can improve it are warranted. For example, trust-building is an emerging focus of current conservation research and thinking (Pretty & Smith 2004; Metcalf et al. 2015; Stern & Baird 2015), and evidence has been provided that trust-building activities among natural resource user groups can improve communication and willingness to adopt sustainable levels of use (Meinzen-Dick et al. 2018). Examples such as these indicate that interventions that build trust and familiarity might affect real-world improvements in human well-being and the environment by creating conditions that favor the effective governance of natural resources. Others have made complimentary observations that positive forest outcomes can be achieved through the implementation of interventions focused on building shared identity and purpose (Wilkie & Painter 2021).

4.3 Existing frameworks and strategic guidance affect CBC outcomes

Consistent with earlier reviews of CBC (e.g., Brooks 2017), we found that many project-level variables influenced CBC outcomes. With regard to the specific strategies and interventions employed, it is widely assumed that sustainable, place-based economic opportunities are critically important to CBC success. However, despite the increased adoption of integrated conservation and development approaches (Roe et al. 2013; Miller 2014) and a significant investment by conservation organizations into sustainable livelihoods, evidence of their effectiveness remains mixed (e.g., Roe et al. 2015; Burivalova et al. 2019). Although positive economic outcomes are frequently reported (e.g., increased employment opportunities or income), many times they are achieved at the cost of negative social outcomes such as conflict or increased wealth inequality (Blundo-Canto et al. 2018). Furthermore, livelihood interventions have not consistently generated benefits, suggesting a need for further research on enabling conditions and unintended consequences, as well as the importance of complimentary interventions, and more thoughtful planning, design, and implementation.

While our analysis was not set up to explore the reasons specific interventions succeeded or failed, we found that economic development was especially important to combined success and that diversification-based approaches (e.g., alternative methods, resources, and occupations) had a significant positive effect. A review of these has led to some key observations. Of note is that livelihood interventions are best leveraged in support of those most vulnerable to conservation-imposed costs (Wright et al. 2016); and that greater emphasis should be placed on participatory planning approaches that solicit the community's input on livelihood opportunities in advance of their implementation, offering better alignment with local needs and priorities and a greater chance for success (Heiner et al. 2019; Sene-Harper et al. 2019). We also reiterate that we found no evidence of a positive effect for compensation-based strategies (e.g., PES), which seems consistent with the variability in evidence reported (e.g., Jayachandran et al. 2017; Burivalova et al. 2019). In short, there remains much to unpack to adequately evaluate the efficacy of different livelihood interventions, including a more thorough analysis of the importance of adequate and equitable benefits, disproportionate costs, and their durability considering alternatives and associated opportunity costs. For example, how lucrative is an acai enterprise compared to a timber lease? Although we attempted to collect some of this information, many of the studies in our sample did not adequately report on them, and evidence gaps remain. Thus, more formal tests of the relative importance of these variables to the success of livelihood interventions and CBC in general are still needed. We identify this as an important future direction.

We also found evidence that capacity-building interventions influence CBC outcomes (Moore et al. 2006), reinforcing widely held assumptions that local capacity is foundational to the success of CBC (Pretty 2003; Pretty & Smith 2004; Ostrom et al. 2009; Lockwood 2010; Agrawal & Benson 2011). Theoretical and empirical evidence suggests that community leaders and institutions can motivate collective action (Glowacki & von Rueden 2015; Warren 2016) and promote effective governance of natural resources through improved coordination, enforcement, compliance, and conflict resolution (Persha et al. 2011; Stein et al. 2011). Beyond this, community leaders and institutions can facilitate social learning and the diffusion of innovations within the community and beyond (Valente & Davis 1999; Mascia & Mills 2018). Strong leadership and institutions have been associated with positive CBC outcomes (Brooks 2017), whereas others have noted that when community leaders and institutions are ineffective, subject to corruption or elite capture, or incapable of coordination with others, CBC can fail (Knight et al. 2016; Warren & Visser 2016).

We found that interventions that strengthened human capital (training or technical assistance) had significant positive effects. Beyond this, we found that other forms of capacity-building focused on social and institutional capital (leadership or governance) or general community well-being, such as health or infrastructure interventions, had potential positive effects. Although our findings suggest only the potential for a positive effect due to health or infrastructure interventions, a range of positive estimates bounded by 0 compliments the findings of a recent study of CBC initiatives in rural Borneo, which showed that such interventions could generate improved health outcomes in addition to carbon sequestration benefits through reductions in illegal logging (Jones et al. 2020).

Although tenure security is foundational to the CBC frameworks we considered (e.g., TNC 2017), we found no evidence of a positive effect despite it being important to our overall model of combined success. Like compensation-based economic development interventions, perhaps this finding reflects the varied evidence presented by others, which highlights the nuanced effects of tenure form and security on human well-being and environmental outcomes (Liscow 2013; Robinson et al. 2014; Buntaine et al. 2015; Tseng et al. 2021). Although

some have found that tenure security can promote positive outcomes for people and nature (Tseng et al. 2021), others have suggested that tenure security alone may be insufficient (Robinson et al. 2014; Vélez et al. 2020) and that the conservation benefits of actions such as titling may diminish with time (Roopsind et al. in review). These findings highlight the importance of tenure security to CBC outcomes in general but raise the possibility that the specific means of doing so and the complimentary activities undertaken might be more important (Agarwala & Ginsberg 2017). A recent global analysis of community forest management supports this interpretation (Hajjar et al. 2021), finding that clear *de facto* rights and the strength of community institutions for natural resource governance had a stronger association with positive social and environmental outcomes than *de jure* rights alone. Collectively, these findings argue for greater emphasis on tenure security interventions such as participatory mapping (Chapin et al. 2005) and the co-implementation of capacity-building interventions such as those that strengthen community-based organizations for natural resource management and provide support for community visioning and land use planning activities (e.g., Heiner et al. 2019).

Similarly, multistakeholder interventions are often a focus of CBC strategy, although we found no evidence of a positive effect. It has been observed that improper implementation of multistakeholder interventions can do more harm than good, for example, by perpetuating existing inequitable power dynamics (Edmunds & Wollenberg 2002; Warner 2007). Given that multistakeholder platforms can promote self-determination and the active participation of previously marginalized groups, an important emphasis of emerging human rights-based frameworks such as the United Nations Declaration on the Rights of Indigenous Peoples (IUCN 2012), we propose that practical insights and methodological advances on how to implement them more effectively will be important to improving the efficacy of these interventions and clarifying their contribution to CBC success (e.g., Kusters et al. 2018).

4.4 Project period and implementation stage affect CBC outcomes

Though both were treated as controls, we found that the period in which a project occurred, and its age had notable effects on CBC outcomes. First, we found that later projects had a significant positive effect on combined success. Many have argued that attention to human wellbeing can generate benefits for people and nature (Bennett et al. 2017; Ellis & Mahrabi 2019), and we posit that shifts in the framing of conservation to be more inclusive and equitable could be one potential explanation for this trend (Chapin 2004; Chan et al. 2007; Kareiva & Marvier 2012). Second, while we did not detect a significant positive effect of project age as observed by others (Brooks 2017), we did observe a potential negative effect for early-stage, very young projects and a potential positive effect for late-stage projects. We interpret this to suggest that CBC projects require a certain minimum maturation before positive human wellbeing and environmental outcomes might be expected. Given that the breakpoints of our variable align with a typical 3-year funding cycle, this would suggest that at least a second round of investment would be required to expect positive outcomes, though sustainable financing and plans to transition to community management and ownership would be important additional considerations.

4.5 Limitations and caveats

We apply a novel analytical approach to our review of the efficacy of CBC and what catalyzes its success. To our knowledge, we are among the first to use machine learning methods to analyze CBC projects and identify the variable most associated with their ability to deliver positive human well-being and environmental outcomes from many promoted by existing practitioner-oriented frameworks. As is well documented, there are general

limitations associated with the comprehensiveness and quality of the CBC literature and its potential reporting bias (Pullin & Stewart 2006). In addition, we acknowledge limitations specific to our process of curating a sample, its resulting size and representativeness, our coding decisions, variable processing and selection criteria, and analytic process.

First, we do not capture the universe of CBC projects but have curated an adequate and reasonable sample of projects from across the globe employing many of the interventions commonly promoted by existing practitioner frameworks. Encouragingly, RFC is amendable to small samples, and our model performed reasonably well on training and test data. Nevertheless, certain geographies (e.g., North America, Australia) and biomes (e.g., freshwater, marine) remain underrepresented in our sample. As a result, it is unclear how much our findings would change with the expansion of our sample, although we offer a transparent and repeatable process for doing so. We identify an expansion of search terms to better capture the diverse literature on this topic and the various perspectives by which it is approached to be an important future direction.

Second, the way in which we constructed and coded our variables has an acknowledged bearing on our results. We accept this as a necessary caveat for conducting such analyses, and as others have done, we provide detailed documentation of the response and explanatory variables we extracted from the literature and how they were defined (see Table S2). Unfortunately, we found that many variables of theoretical significance and hypothesized importance to CBC outcomes were unavailable for our modeling effort (see the evidence gaps identified in Table S4, with definitions in Table S2). For example, “meaningful engagement and participation” is a common recommendation for effective CBC (Vermeulen & Sheil 2006; Persha et al. 2011; Andrade & Rhodes 2012). Yet we found it to be ill-defined and inadequately reported in our sample. We attempted to characterize meaningful engagement and participation as a function of community consultation in project design, community integration in project management, and community involvement in project activities. However, each of these variables had missing data proportions that precluded their further consideration. Observations such as these reiterate the need for better monitoring and reporting of key components and assumptions, as well as further analysis of their importance to CBC outcomes. We identify this as an important future direction.

Third, analytical methods such as RFC have certain advantages over conventional analytical approaches, which we reiterate is a novel contribution of this work; nevertheless, certain limitations and caveats exist. Foremost is that RFC is challenged by overly small and unbalanced samples. We address this by imputation of missing values to avoid further reductions in sample size, synthetic matching to balance training data, and bootstrapping to improve model performance and provide a means of calculating confidence intervals appropriate to the data. To address the implications of these analytic decisions, we provide additional analyses in the supplement that explore the sensitivity of our results to the 1) assignment of test and training data, 2) balancing of the training data, 3) missingness and imputation among our explanatory variables, and 4) response variable definition (see Figures S5-S7 and Table S5). In general, these analyses are supportive of the approach taken.

Further, we use RFC to identify variables most important to combined success, but because this method only identifies *which* variables are important to prediction but *not how*, we pair it with an estimation of accumulated local effects. We qualify our results by emphasizing that the variables we considered were only a set of possibilities motivated by existing theoretical and applied CBC frameworks, which were further reduced by processing and selection processes (see Table S4). The relative importance and effects reported are contingent on this as well as our overall analytic process (see Table S1). As a result, we do not claim to have captured all

the variables that could be important to CBC outcomes in and beyond our sample, nor do we claim causality for the 17 variables ultimately included. Like any method, RFC is sensitive to the analytic dataset, but the variables that emerged from our modeling effort are important predictors of combined success for the 128 CBC projects in our sample. Taken together and situated with other evidence on CBC efficacy, we believe our results provide important advances relevant to the design and implementation of CBC projects more broadly.

5. Conclusion

Mounting threats to places of conservation value long stewarded by Indigenous Peoples and local communities make CBC projects that generate positive outcomes for people and nature now more imperative than ever. A practical lens and new analytic approaches that allow rigorous exploration of the myriad factors associated with the social, economic, and environmental outcomes of CBC can provide valuable insights for researchers, policymakers, and practitioners confronting the challenges ahead. We contribute to the ongoing effort to build an evidence base for effective CBC, primarily through our application of exploratory machine learning methods, alignment with existing practitioner frameworks, and emphasis on actionable leverage points. Some of our findings complement previous efforts. Specifically, our results reinforce the importance of capacity-building interventions and continued investments beyond a typical funding cycle. Some of our findings add weight to what remains a mixed evidence base. For example, our results suggest that economic development interventions are important to project success, specifically diversification-focused approaches such as alternative livelihoods, but positive effects for compensation-based livelihoods such as PES and interventions related to tenure security and multistakeholder platforms were lacking lacked evidence. Last, some of our findings are novel. Our results suggest that national contexts supportive of effective local governance, community characteristics conducive to social cohesion and collective action, and projects attentive to building trust are favorable to success. Such findings can help catalyze greater success in CBC, but the need for more research remains. Outstanding questions are many, but most immediately include 1) how robust these predictors of success are across a greater range of socio-ecological systems and contexts and 2) how influential variables currently unaccounted for in our model are to predicted outcomes. We propose that closer attention to the important variables and evidence gaps identified by our study can help focus future monitoring and evaluation efforts, evolve stronger CBC practitioner frameworks, and contribute to a more effective and evidence-based practice that supports equitable and community-centered stewardship of critical conservation landscapes.

Declarations

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CONFLICT OF INTEREST

The authors declare that there are no conflicts of interest.

AUTHOR CONTRIBUTIONS

BF, ND and CMK conceived and designed the study. BF and KAP performed the preliminary search and screening. BF, KAP and ND coded the inclusion set. BF, ND and CMK conducted the secondary review. BF performed the analysis and interpreted the results with assistance from CEL and CMK. BF led writing of the manuscript. All authors critically revised the manuscript and gave final approval for the submitted version.

ETHICS STATEMENT

This study did not involve any experiments on animal or human subjects.

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DATA AVAILABILITY & SUPPLEMENTARY INFORMATION

The data used for this analysis are summarized below:

1. **Administrative boundaries:** A global dataset of administrative boundaries was sourced from the Global Administrative Areas (GADM) spatial database version 2.8, which can be found here: https://gadm.org/
2. **National-level variables:** In addition to the data coded in the review, several national-level indicators were obtained from existing data sources and considered explanatory variables in the RFC model. Each is available from its source:

    1. Legal Security of Indigenous Lands Index, Landmark: http://www.landmarkmap.org/data/
    2. World Governance Indices (Political Stability, Voice and Accountability, Control of Corruption, Regulatory Quality), World Bank: http://info.worldbank.org/governance/wgi/#home
    3. Human Development Index, United Nations Development Program: http://hdr.undp.org/en/data
    4. Environmental Democracy Index, World Resources Institute: https://environmentaldemocracyindex.org/about/resources

3. **Data:** See supplementary information for sample data. Additional data can be obtained from the primary author upon reasonable request.
4. **Code:** The R code used in this analysis can be obtained from the primary author upon reasonable request.

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Figures

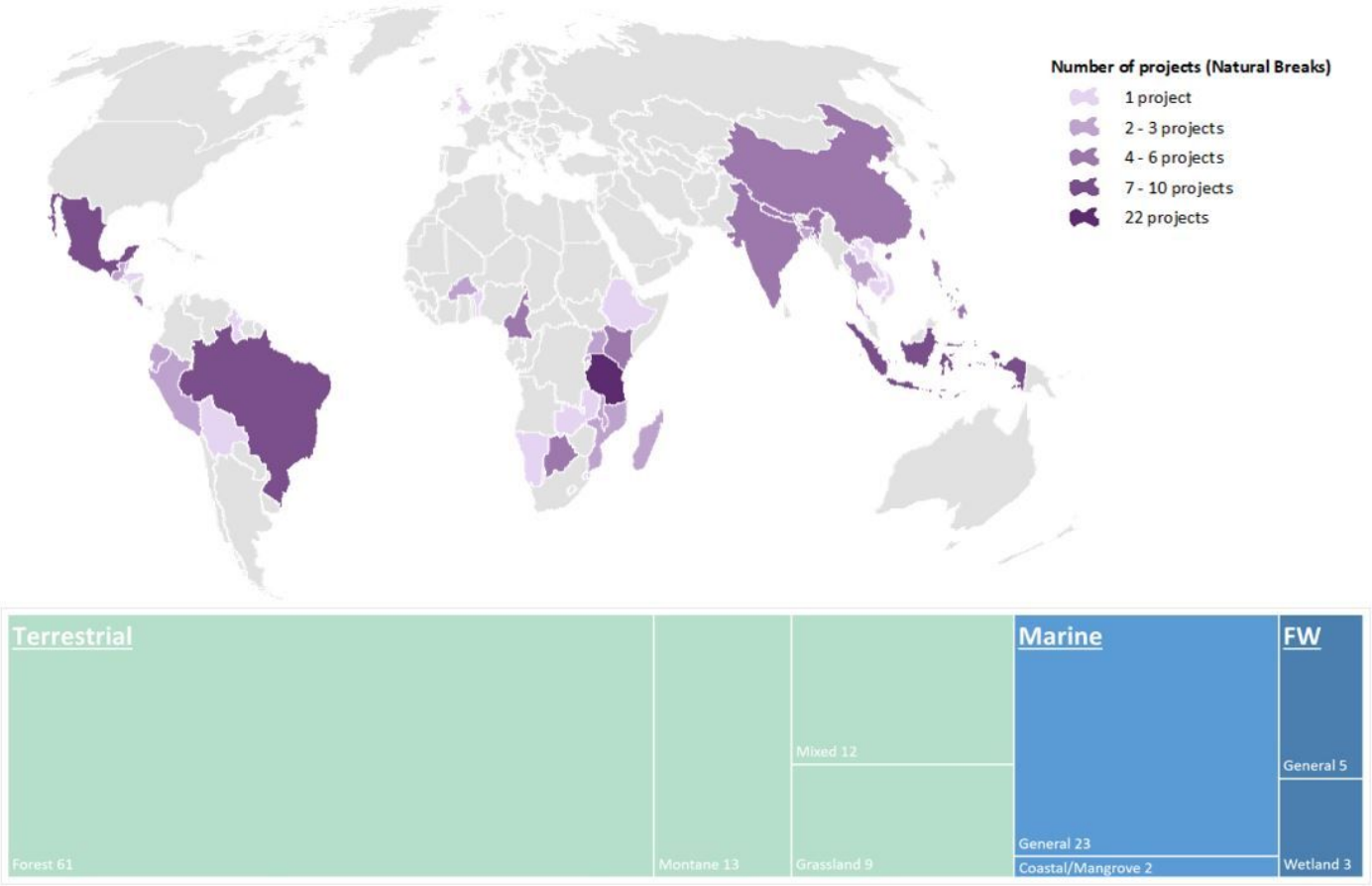

Figure 1

Geographies and conservation biomes represented in the sample. See SI for references (Table S7).

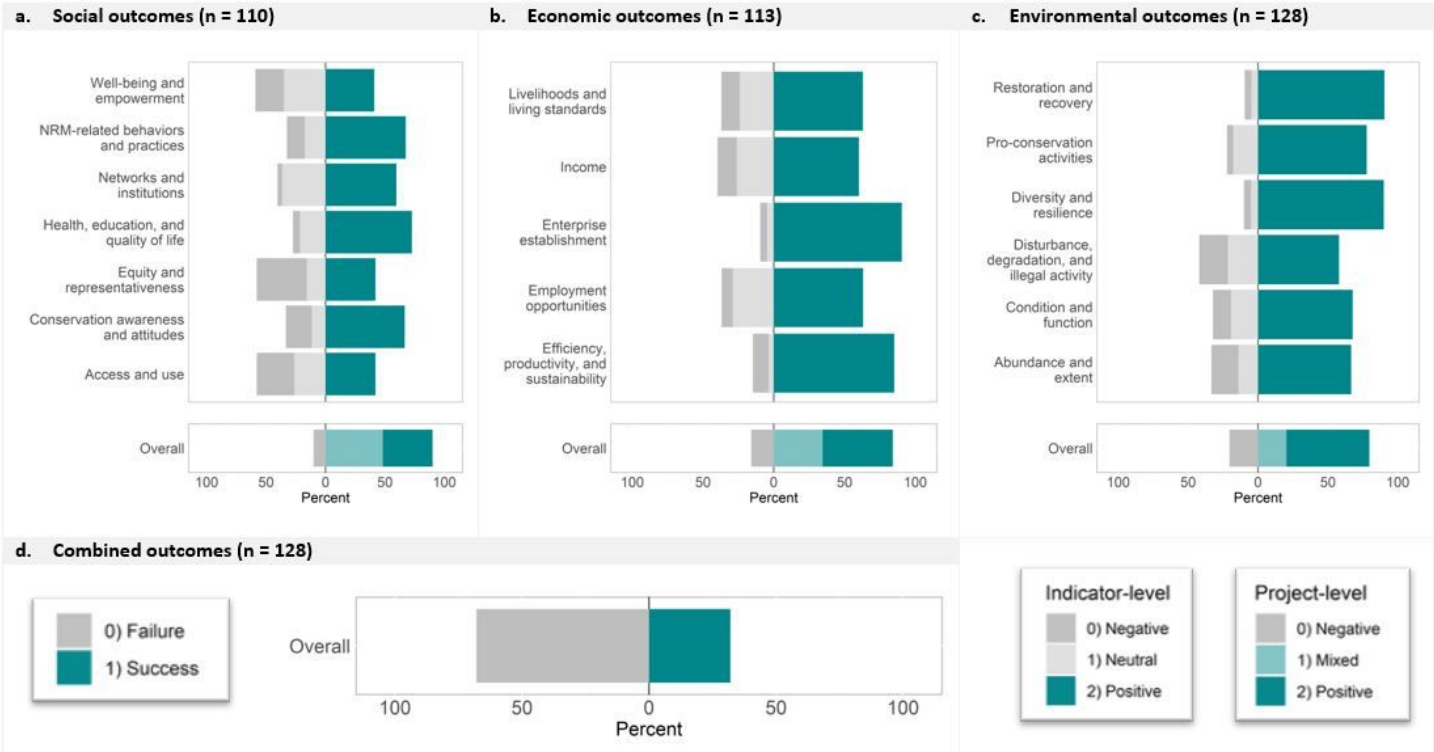

Figure 2

Social (a), economic (b), and environmental (c) outcomes. Indicators reported for each project are summarized in the top half of each panel. Indicators were scored as “negative”, “neutral” or “positive.” Project-level outcomes are shown in the bottom half of each panel and are an aggregation of all the indicators measured for that project. Project-level outcomes were scored as “negative” if all indicators were negative, negative/neutral, or neutral only; “mixed” if there were some positive indicators; and “positive” if all indicators were positive. For combined outcomes (d), our response variable in subsequent modeling, projects were scored as a “success” if their human well-being (social and/or economic) and environmental outcomes were positive and a “failure” if otherwise. See Figure S2 for alternative heatmap graphics showing the percentage, mean, and standard deviation for indicator and project-level outcomes.

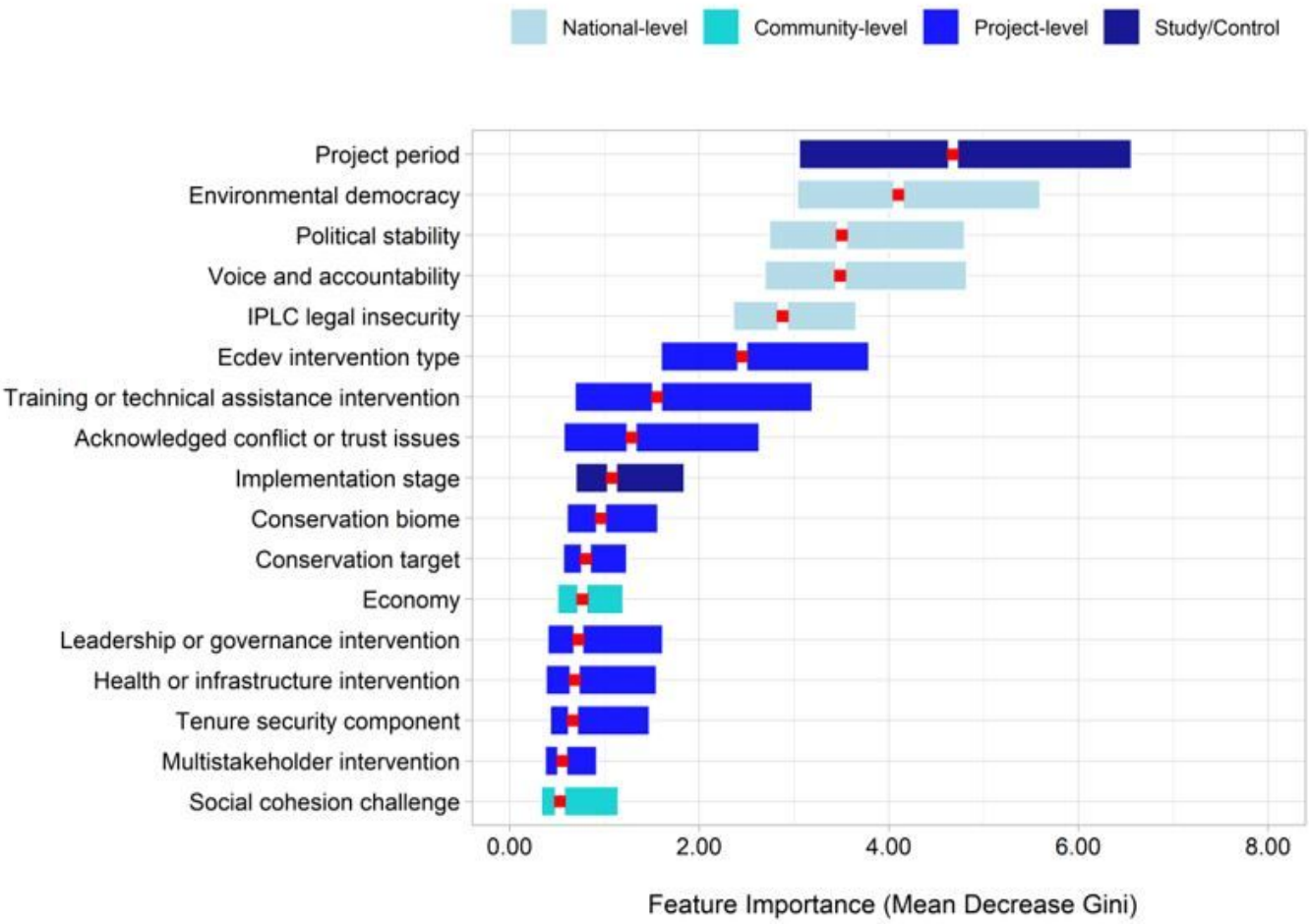

Figure 3

Bootstrap estimated ($\mathbf{B}$ = 1000) feature importance scores for variables of the Random Forest Classification (RFC) model of combined success (see Figure 2d). Feature importance scores are relative and describe which variables are most important to model prediction. Higher values indicate greater importance. We use Mean Decrease Gini as a measure of feature importance, which can be interpreted as the mean decrease in node impurity achieved by inclusion of the variable in the model (averaged across all individually grown trees). This measure describes how good the variable is at parsing the training data into homogenous groupings of the response (success or failure). The red symbol is the median of bootstrap estimates, and the bar represents the percentile-based 90% confidence interval, which we consider an acceptable level of uncertainty given the relatively small sample size. Variables are ranked from highest to lowest feature importance, and each is color-coded by level per the legend at top. See Table 1 for definitions and hypothesized effects for each variable and Figure S4 for a comparison of alternate feature importance measures.

Figure 4

Bootstrap estimated ($\mathbf{B}$ = 1000) accumulated local effects (ALE) for national-level (a), community-level (b), project-level (c), and control variables (d). The y-axis of each plot is centered on the mean prediction. The value plotted is interpreted as a change in the probability of combined success associated with a specific value of the variable (Molnar 2019). ***For continuous variables***, the light blue lines show individual bootstrap estimates, the dark blue line is the median of bootstrap estimates, the gray envelope represents the percentile-based 90% confidence interval, and the dotted red line is a smoothed loess curve. ***For categorical variables***, the light blue barcode shows individual bootstrap estimates, the dark blue symbol is the median of bootstrap estimates, and the blue error bar represents the percentile-based 90% confidence interval, which we consider an acceptable level of uncertainty given the relatively small sample size. Statistical significance is indicated by confidence intervals that do not overlap mean-center. Significant estimates are proceeded by (**). Same-sign estimates with an upper or lower limit bounded by 0 are proceeded by (*). Plots are shown for each variable, grouped by level, and ordered from highest to lowest feature importance (see Figure 3).

Supplementary Files

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