Catalyzing Success in Community-based Conservation

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Systematic Review

Keywords: Community-based conservation, conservation evaluation, conservation outcomes, evidence-based conservation, machine learning, random forest classification, accumulated local effects

Posted Date: March 16th, 2022

DOI: https://doi.org/10.21203/rs.3.rs-1425173/v2

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 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.

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. 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). 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.

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 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 because it requires little to no *a priori* knowledge about the relative importance of different explanatory variables, can model correlated variables and nonlinear relationships common with socioecological data, and better detect small individual effects. As a result, our analysis provides novel insights into what might catalyze CBC success. This information is needed to develop effective strategies and identify evidence gaps that must be filled to strengthen the evidentiary backing of existing CBC frameworks.

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 (ALEs) to describe how each affects 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).

Curating, coding, and processing the sample

Our sample pulls from diverse sources of evidence, ranging from peer-review journals, books, theses, dissertations, conference proceedings and technical reports. Studies must have reported human well-being

and environmental outcomes (Appendix B1). Methodological approaches range from case studies to quasi-experimental research designs and included qualitative and quantitative indicators. Because we permitted diverse evidence, we 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 (Appendix A1, B2).

We first considered the projects from previous related reviews that examined strategies and interventions relevant to CBC frameworks we were specifically interested in testing (TNC 2017; Mahajan et al. 2021). 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 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 employed best practices to expand 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 (Petrokofsky 2018) and conducted our search in Google Scholar via Publish or Perish software (Harzing 2007). Like 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 SI (Appendix A7).

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 (Appendix B2). We used an adaptive coding scheme and retained as much overlap with previous reviews as possible.

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 (Pullin & Stewart 2006; Humphries et al. 2018). Most of our explanatory variables 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. Like other systematic reviews (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 (Appendix A6). We used 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 (Stekhoven 2013). We estimated imputation error (IE) 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, resulting in the exclusion of three explanatory variables.

Last, we performed a second blind review of a stratified random sample of 20% of our inclusion set to calculate interrater reliability (IRR) for each coded variable (Collaboration for Environmental Evidence 2013). We calculated Cohen’s Kappa (Cohen 1960; Garner et al. 2019), and used an IRR < 0.60 as an indicator of less than moderate agreement (McHugh 2012), resulting in the exclusion of six explanatory variables.

Random forest classification

We summarized indicator and project-level outcomes (Bryer & Speerschneider 2016; Wickham 2016), then employed RFC (Breiman 2001), a specific implementation of classification and regression tree (CART) analysis (WeiYin 2008; Humphries et al. 2018) to identify the variables most important to combined success in human well-being (social and/or economic) and environmental outcomes. RFC provides a flexible, nonparametric approach to exploring the effects of numerous theoretically important explanatory variables on CBC project outcomes. A key advantage is its ease of implementation and robustness to challenges common to the socioecological data typically available for CBC projects (Cutler et al. 2007).

Modeling combined success

Our response variable for the RFC model was “combined success.” Our explanatory variables come from the 57 variables we coded that were informed by previous reviews and existing CBC frameworks (Appendix B2). In sum, 28 explanatory variables met our inclusion criteria (NDP ≤ 0.30, IE ≤ 0.30 and IRR ≥ 0.60 (Appendix B4). Prior to modeling, our project sample (n = 128) was parsed into training and test data. Test data were established from a randomly selected 20% of the original sample (n = 26); and had balanced 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). RFC is adversely affected by unbalanced training data (Shaikhina et al. 2019), and balancing can significantly improve the performance of RFC. Thus we balanced the training data using the synthetic matching algorithm SMOTE (Chawla et al. 2002; Torgo 2010), and offer a comparison of model performance measures between the original, unbalanced training data, and a number of different balanced training datasets, as well as an analysis of the sensitivity of our results to different initial training and test assignments in the SI (Appendix A5, B5).

We then ran bootstrapped ($\mathbf{B}$ = 1000) RFC models on our best performing balanced training data and optimized model parameters using grid search (Liaw & Wiener 2002; Reif et al. 2012; Paluszynska et al. 2019). An iterative variable selection process aimed at improving model performance reduced the 28 variables we initially considered to 17 through the following steps: 1) pruning of redundant variables via selection of a representative from within the suite based on feature importance scores and 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 ≤ 0.50 mean decrease Gini.

Model performance and prediction

We report several measures of performance for the RFC model to assess 1) the proportion of all cases correctly predicted by the model (accuracy); 2) the proportion of actual successes correctly predicted to identify omission errors (recall); and 3) the proportion of predicted successes that were actually successes to identify commission errors (precision) (Frank 2019). We also derived receiver operating characteristic (ROC) and area under the curve (AUC) statistics to illustrate the diagnostic ability of the model as a binary classifier (Sing et al. 2005; Ballings & Van den Poel 2013). We bootstrap estimated ($\mathbf{B}$ = 1000) each of these measures to assess the model's fit to the training data, as well as its performance on test data holdout (Appendix A3). We accept ROC-AUC ≥ 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 improved from 0.58 (0.47, 0.67) to 0.70 (0.60, 0.79).

Estimating effects

To aid in effect interpretation, we calculated bootstrap estimated ($\mathbf{B}$ = 1000) accumulated local effects (ALEs) for each variable in the RFC model (Apley 2018; Molnar et al. 2018; Molnar 2019). ALE plots illustrate a variable's overall effect on the predicted outcome, and allow for visualization of the patterns and trends in combined success associated with individual variables (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 an exploratory analysis of overall and two-way interactions between variables in the SI (Appendix A8).

Results

Sample description

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, Appendix B7). 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. Thirty-eight percent of projects reported quantitative indicators, 34% qualitative, 26% author-reported or secondary sources, and two percent had a mix of indicator types with no clear majority. Forty-nine percent of projects reported indicators with treatment or time controls, 43% with no control, and eight percent 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 collected primary data (72%), using methodological designs considerate of at least one or more controlling variables (58%) (Appendix AI).

Project 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, Appendix A2a). 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. Descriptions and sample sizes of indicator categories are in the SI (Appendix B3).

Of the 113 projects that reported economic outcomes, 50% had all positive indicators, and an additional 35% were mixed (Fig. 2b, Appendix A2b). 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, Appendix A2c). Like 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.

Variable importance

Bootstrap estimated ($\mathbf{B}$ = 1000) feature importance scores for the 17 explanatory variables of our RFC model are shown in Fig. 3 (Appendix B6). 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) (Appendix A3).

Variable effects

Bootstrap estimated ($\mathbf{B}$ = 1000) ALEs for each of these 17 variables are shown in Fig. 4. Most variables showed trends consistent with their hypothesized effect (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). 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%).

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).

We found that 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). Regarding 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%).

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. In addition to the effects of project period and implementation stage summarized in the SI (Appendix C), 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 project-level interventions at the discretion of conservation practitioners have a positive effect on human well-being and environmental outcomes. Our findings offer insights into factors important for CBCs to deliver benefits for people and nature, provide evidentiary support for existing CBC frameworks, and clarify evidence gaps requiring further study.

National contexts and local governance

The importance of context to CBC outcomes 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 found no 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 may represent 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. For example, greater investment in capacity-building efforts that foster community engagement and representation in decision-making processes may be important 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).

Social cohesion and trust

Social cohesion and collective action are foundational to many CBC frameworks (Olson 1965; Agrawal & Ostrom 2001; Colfer 2007; Bodin 2017; Mahajan et al. 2021). 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).

We found that social cohesion challenges had a potential negative effect on CBC outcomes, whereas acknowledgement of conflict or trust issues 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 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 there is evidence 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).

Existing frameworks and strategic guidance

Consistent with earlier reviews of CBC, we found that many project-level variables influenced CBC outcomes. A broad literature assumes 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 need for 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. Existing research suggests that livelihood interventions are best leveraged in support of those most vulnerable to conservation-imposed costs (Wright et al. 2016), and participatory planning approaches that solicit the community's input on livelihood opportunities in advance of their implementation can better align with local needs and priorities, resulting in a greater chance for success (Heiner et al. 2019; Sene-Harper et al. 2019). Further, 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, more work is needed to unpack 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 such information from the studies in our sample, many 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 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 associated with health or infrastructure interventions, a range of positive estimates bounded by 0 complements the findings of a recent study of conservation and healthcare related initiatives in rural Borneo (Jones et al. 2020).

Although tenure security is foundational to many CBC frameworks (e.g., TNC 2017), we found no evidence for a positive effect. 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). Our 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 complementary 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, we found no evidence of multistakeholder interventions having a positive effect. 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 UNDRIP (IUCN 2012), 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).

Limitations and caveats

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. There are general limitations associated with the comprehensiveness and quality of the CBC literature and its potential reporting bias (Pullin & Stewart 2006), and like all studies, we note several limitations that future work can improve on.

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. 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, our findings may be sensitive to a larger and more diverse sample. 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, our results may be sensitive to variable construction and coding. For transparency, we provide detailed documentation of the response and explanatory variables we extracted from the literature and how they were defined (Appendix B2). Unfortunately, we found that many variables of theoretical significance and hypothesized importance to CBC outcomes were unavailable for our modeling effort (Appendix B4). For example, “meaningful engagement and participation” is a common, though ill-defined recommendation for effective CBC (Vermeulen & Sheil 2006; Persha et al. 2011; Andrade & Rhodes 2012). 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 them from 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.

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, 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 SI 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 (Appendix A5-7, B5).

Further, we use RFC to identify variables most important to combined success, but because it only identifies *which* variables are important to prediction but *not how*, we also estimate accumulated local effects. We

qualify our results by emphasizing that the variables considered were only a set of possibilities motivated by existing CBC frameworks, which were further reduced by variable processing and model selection processes (Appendix B4). The relative importance and effects of the variables reported are thusly contingent on this process (Appendix B1). 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. However, 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.

Mounting threats to places of conservation value long stewarded by IPLCs 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, such as reinforcing 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, especially diversification-focused strategies, are important to combined success, but evidence of a positive effect for compensation-based livelihoods such as PES, or interventions related to tenure security and multistakeholder platforms was lacking. Last, some of our findings are novel. Our results suggest that national contexts supportive of effective local governance, and community characteristics and projects promoting trust and social cohesion are favorable to success. Our results can help catalyze greater success in CBC, but the need for more research remains. There are many outstanding questions, 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

SUPPORTING INFORMATION

Additional information is available online in the Supporting Information section at the end of the online article. The authors are solely responsible for the content and functionality of these materials. Queries (other than absence of the material) should be directed to the corresponding author.

ACKNOWLEDGMENTS

We would like to thank several individuals for contributions to the planning, review, and presentation of this work, including A. Aldous, A. Akalleq-Burgess, R. Cortez, M. Fariss, E. Meyers-Madeira, C. Schwinn, and members of the Alliance for Conservation Evidence and Sustainability (ACES). Financial and administrative support for this effort was provided by generous contributions from an anonymous private donor; the Global Conservation in Partnership with Indigenous Peoples and Local Communities Team; and Protect Oceans, Lands and Waters Science Team of The Nature Conservancy.

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 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

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 SI 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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Tables

Table 1 is in the supplementary files section.

Figures

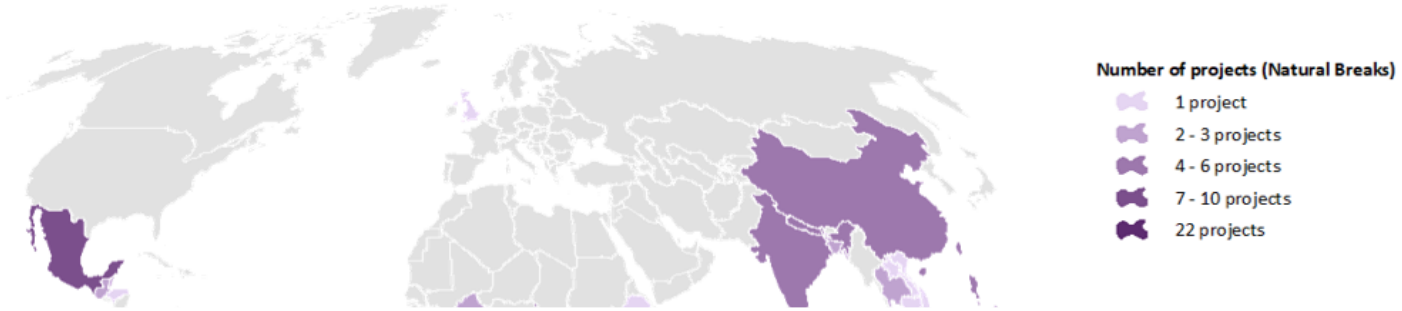

Figure 1

Geographies and conservation biomes represented in the sample (see references in Appendix B7).

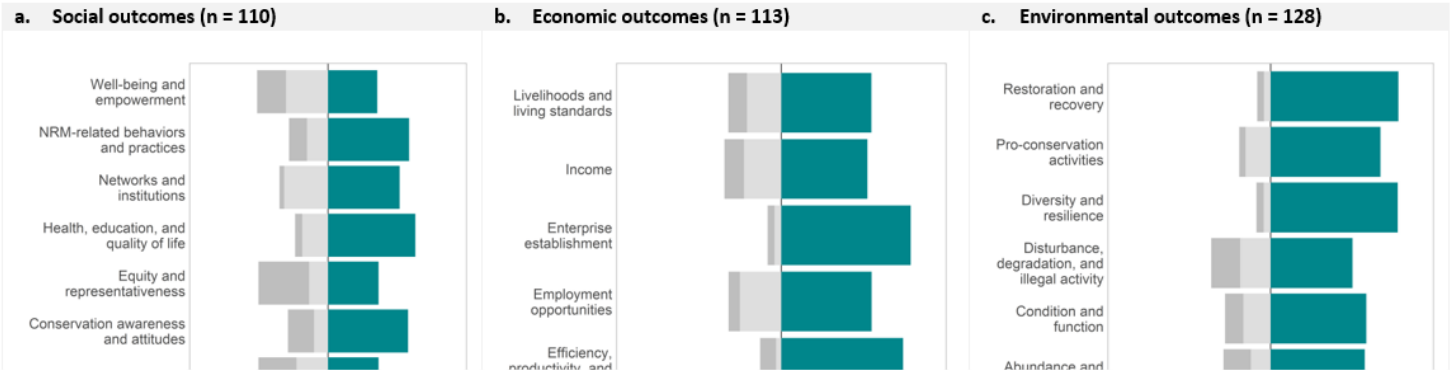

Figure 2

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. Heatmaps showing the percentage, mean, and standard deviation for indicator and project-level outcomes are in the SI (Appendix A2).

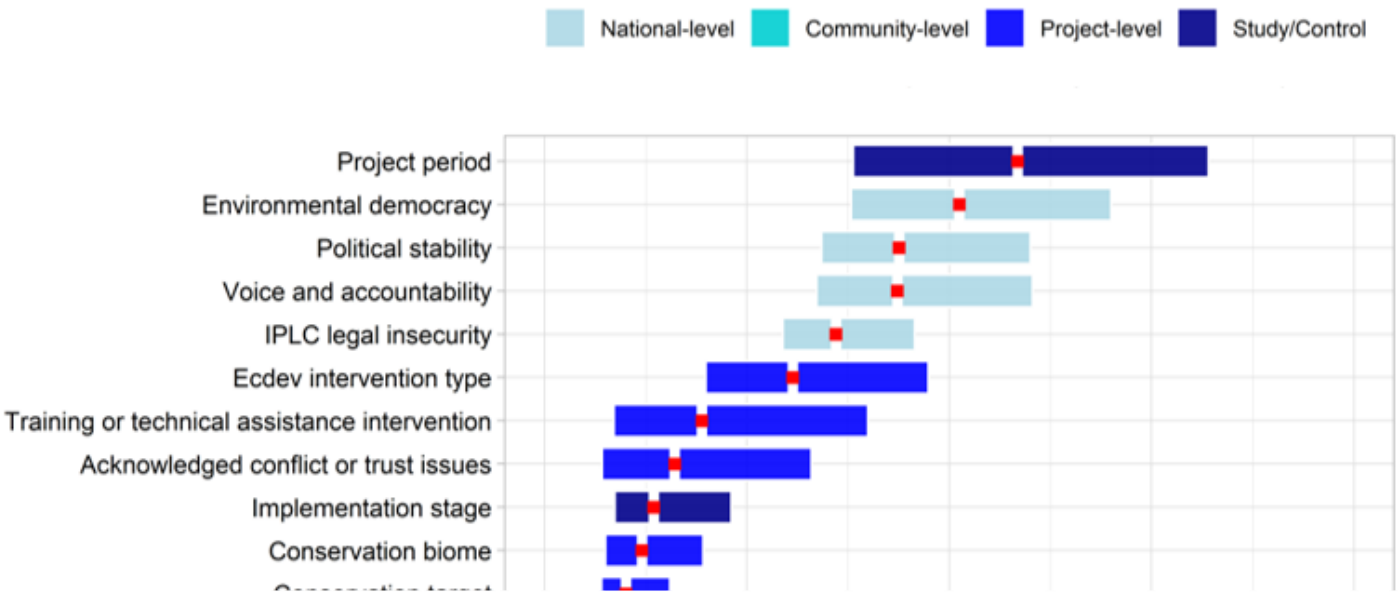

Figure 3

Bootstrap estimated ($\mathbf{B}$ = 1000) feature importance scores for variables of the random forest classification (RFC) model of combined success (Fig. 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. Definitions, hypothesized effects, and a comparison of alternate feature importance measures are provided elsewhere (Table 1, Appendix A4).

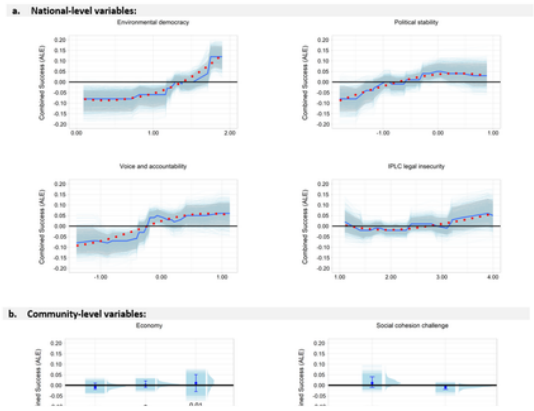

Figure 4

Bootstrap estimated ($\mathbf{B}$ = 1000) accumulated local effects (ALEs) for national-level (a), community-level (b), project-level (c), and control variables (d). Plots are ordered from highest to lowest feature importance (Fig. 3). 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 (**). Estimates with a confidence interval limit bounded by 0 are proceeded by (*).

Supplementary Files

This is a list of supplementary files associated with this preprint. Click to download.

- CatalyzingSuccessSupportingInformation.pdf
- Table1.docx