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Conservation Methods

A Bayesian hierarchical approach to quantifying stakeholder attitudes toward conservation in the presence of reporting error

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Abstract: Stakeholder support is vital for achieving conservation success, yet there are few reliable mechanisms to monitor stakeholder attitudes toward conservation. Approaches used to assess attitudes rarely account for bias arising from reporting error, which can lead to falsely reporting a positive attitude toward conservation (false-positive error) or not reporting a positive attitude when the respondent has a positive attitude toward conservation (false-negative error). Borrowing from developments in applied conservation science, we used a Bayesian hierarchical model to quantify stakeholder attitudes as the probability of having a positive attitude toward wildlife notionally (or in abstract terms) and at localized scales while accounting for reporting error. We compared estimates from our model, Likert scores, and naïve estimates (i.e., proportion of respondents reporting a positive attitude in at least 1 question that was only susceptible to false-negative error) with true stakeholder attitudes through simulations. We then applied the model in a survey of tea estate staff on their attitudes toward Asian elephants (*Elephas maximus*) in the Kaziranga–Karbi Anglong landscape of northeast India. In simulations, Bayesian model estimates of stakeholder attitudes toward wildlife were less biased than naïve estimates or Likert scores. After accounting for reporting errors, we estimated the probability of having a positive attitude toward elephants notionally as 0.85 in the Kaziranga landscape, whereas the proportion of respondents who had positive attitudes toward elephants at a localized scale was 0.50. In comparison, without accounting for reporting errors, naïve estimates of proportions of respondents with positive attitudes toward elephants were 0.69 and 0.23 notionally and at local scales, respectively. False (positive and negative) reporting probabilities were consistently not 0 (0.22–0.68). Regular and reliable assessment of stakeholder attitudes–combined with inference on drivers of positive attitudes–can help assess the success of initiatives aimed at facilitating human behavioral change and inform conservation decision making.

Keywords: bias, latent state models, misreporting rates, monitoring, perception, stakeholder engagement

Una Estrategia de Jerarquía Bayesiana para Cuantificar las Actitudes de Grupos de Interés hacia la Conservación en Presencia de Errores de Información

Resumen: El apoyo de los grupos de interés es vital para alcanzar el éxito en la conservación, sin embargo, existen pocos mecanismos confiables para monitorear la actitud de los grupos de interés hacia la conservación. Las estrategias que se usan para valorar las actitudes de los grupos de interés pocas veces toman en cuenta el sesgo que surge de errores en la información, lo cual puede resultar en un falso reporte de actitudes positivas hacia la conservación (error falso positivo) o en que no se reporte una actitud positiva cuando el respondiente tiene una actitud positiva hacia la conservación (error falso negativo). Usamos un modelo de jerarquía bayesiana, construido a partir del desarrollo aplicado en la ciencia de la conservación, para cuantificar las actitudes de los grupos de interés como la probabilidad de tener, teóricamente (o en términos abstractos) y a escalas locales, una actitud positiva hacia la vida silvestre mientras se compensa el error de información. Comparamos mediante simulaciones las estimaciones de nuestro modelo, los puntajes de Likert y las estimaciones ingenuas (es decir, la proporción

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de los respondientes que reportaron una actitud positiva en al menos una pregunta que se encontraba solamente susceptible al error falso negativo) con las verdaderas actitudes de los grupos de interés. Después aplicamos el modelo al censo realizado al personal de una finca de té sobre sus actitudes hacia los elefantes asiáticos (*Elephas maximus*) en el paisaje de Kaziranga-Karbi Anglong al noreste de la India. En las simulaciones, las estimaciones de las actitudes de los grupos de interés hacia la vida silvestre generados por el modelo bayesiano estuvieron menos sesgados que las estimaciones ingenuas o los puntajes de Likert. Después de considerar los errores de información, estimamos una probabilidad de 0.85 de que los respondientes teóricamente tuvieran una actitud positiva ante los elefantes en el paisaje de Kaziranga, mientras que la proporción de respondientes con actitudes positivas hacia los elefantes a escalas locales fue de 0.50. Como contraste, sin considerar los errores de información, las estimaciones ingenuas de la proporción de los respondientes con actitud positiva hacia los elefantes fueron de 0.69 y 0.23 teóricamente y a escalas locales, respectivamente. El reporte de falsos (positivos y negativos) en las probabilidades constantemente no fue 0 (0.22 – 0.68). La valoración regular y confiable de las actitudes de los grupos de interés – combinada con la inferencia sobre los conductores de estas actitudes positivas – puede ayudar a evaluar el éxito de las iniciativas enfocadas en facilitar cambios en el comportamiento humano y en informar a las decisiones de conservación.

Palabras Clave: modelos de estado latente, monitoreo, participación de grupos de interés, percepción, sesgo, tasas de desinformación

Introduction

With widespread habitat loss and fragmentation, wildlife increasingly share space and interact with people. Occasionally, this can lead to conflict detrimental to both people and wildlife (Woodroffe et al. 2005). Repeated conflicts can foster negative stakeholder attitudes toward wildlife (Dickman 2010), which, in turn, can lead to human behaviors that hinder species persistence (Dickman 2010; Goswami et al. 2014). In the long term, negative attitudes toward wildlife can aggravate conflict and ultimately detract from conservation goals (Dickman 2010; Goswami & Vasudev 2017). Indeed, stakeholder support is recognized as an important determinant of the long-term success of conservation programs (Bennett et al. 2017). However, there is need for more reliable mechanisms to monitor stakeholder attitudes (Kansky et al. 2014; Sterling et al. 2017). Developing scientific approaches to do so is integral to reliably assessing stakeholder attitudes and gaining deeper understanding of changes in stakeholder attitudes across space, time, or individuals. Ultimately, positive stakeholder attitudes toward wildlife are essential to successful conservation.

Most simplistically, a person's attitude toward wildlife can be defined as whether the person is inclined to respond positively toward wildlife or not (Kansky et al. 2014). Typically, attitudes have been quantified as the proportion of people who profess positive attitudes toward wildlife, as assessed through questionnaire surveys (Treves et al. 2013; Kansky et al. 2014). Some surveys may also quantify people's attitudes in a nonbinary manner, along a scale ranging from positive, to neutral, to negative (Røskaft et al. 2007; Bruskotter et al. 2009; Treves et al. 2013).

Questionnaire surveys, however, may not accurately reflect a person's attitude (Fisher 1993; Nuno & St. John 2015). This discrepancy between the recorded and true attitude of a person may lead to 2 forms of bias: positive, when a person intentionally or subconsciously falsely professes a positive attitude toward wildlife, and negative, when a person reports a nonpositive attitude toward wildlife when believing otherwise. The former bias is likely to occur when there is pressure to respond positively toward wildlife, for instance, if surveyors are from conservation institutions. Positive bias is particularly important to recognize because it leads to an overly optimistic view of stakeholder attitudes toward conservation. The 2 forms of bias may also arise due to peer pressure, the perception that being wildlife-friendly is a positive behavioral attitude, a desire to appease people or surveyors, or an expectation of financial or other forms of compensation for losses to wildlife (Fisher 1993; Nuno & St. John 2015). Irrespective of the reason, these sources of bias are important to acknowledge and account for to reliably assess or identify factors influencing people's attitudes toward wildlife.

This potential false reporting reflects an often-encountered problem in conservation research: sources of observational bias result in an imperfect assessment of the true system state (here, the attitude of a person toward wildlife) and significantly affect inference (Williams et al. 2002). Simulation studies demonstrate that observational bias is a substantial problem that can result in misleading inference about estimated parameters and the effect of underlying factors on these parameters (Williams et al. 2002; Gu & Swihart 2004). One way in which false-reporting bias has been addressed in social surveys is to average the attitudinal scores of a respondent across multiple observations, or questions, within the same questionnaire. Perhaps a more robust method would be to formally estimate and account for reporting error while estimating attitudes through a hierarchical modeling approach (Williams et al. 2002; Royle & Dorazio 2008), a field of study that has seen increased development and application in recent years (MacKenzie et al. 2002; Williams et al. 2002; Miller et al. 2011).

We adopted a Bayesian hierarchical approach to separate the processes driving patterns of stakeholder attitudes toward wildlife (or conservation) from observational biases arising from reporting error. We considered attitude a latent binary state variable; thus, a person may be positive toward wildlife or not during the survey period. The propensity of a person to have a positive attitude toward wildlife, then, was our parameter of interest, even while recognizing that the attitude of a person is not directly observable. We further recognize that attitude can vary such that a person may be notionally positive toward wildlife (i.e., positive in relatively abstract terms that do not directly relate to the respondent's reality) but not have a positive attitude at a localized scale, where they may be directly and tangibly affected by such species or their conservation. For example, people may in general want elephants to persist into the future but may not want them in or near their village. Similarly, a person may think lions are a majestic animal but have concerns about the species killing their cattle. These 2 perspectives align loosely with tolerance at the localized scale and with value orientation and empathy at the notional level (Kansky et al. 2016). We prefer to use the more neutral term "attitude" over tolerance because "tolerance" intrinsically associates a cost (potential or actual) with wildlife presence (Kansky et al. 2016). We investigated the utility of a hierarchical model to estimate the probability of positive attitudes notionally and at the localized scale while accounting for reporting error. We then assessed people's attitudes toward the Asian elephant (*Elephas maximus*) in tea estates in northeast India as a practical example of the model's utility.

Methods

Hierarchical Model of Attitudes Toward Wildlife

Our primary parameters of interest were 2 latent state variables. The first was the state of a person indicating whether the person had a positive attitude toward wildlife notionally (i.e., generally and at coarse or nonspecified scales, not specific to the respondent's location). Consider that α_i represents the attitude state of person i toward wildlife notionally, such that $\alpha_i = 1$, if the person has a positive attitude toward wildlife notionally and 0 if the person does not have a positive attitude toward wildlife notionally. Let $\boldsymbol{\alpha} = (\boldsymbol{\alpha}_1, \boldsymbol{\alpha}_2, \boldsymbol{\alpha}_3,..., \boldsymbol{\alpha}_n)$ be a vector denoting the states of n people in a sampled population with respect to their attitude toward wildlife notionally. Let ψ be the probability of a person in the sampled population having a positive attitude notionally toward wildlife. Thus, $\boldsymbol{\alpha}$ follows a binomial distribution with probability ψ and size n (definition of terms and parameter tabulation are in Supporting Information).

Our second latent parameter is the state of a person indicating whether they have a positive attitude toward wildlife at a localized scale, that is, at the scale of the person's district, village, community lands, or personal landholding. We assumed a person could have a positive attitude toward wildlife at a local scale only if the person was positive toward wildlife notionally. Thus, given that $\boldsymbol{\alpha}_i = 1$ (positive attitude notionally), a person i may or may not have a positive attitude toward wildlife at the local scale. Let λ_i represent the person's attitude toward wildlife at the scale of their neighborhood, where $\lambda_i = 1$, if the person has a positive attitude toward wildlife in their neighborhood and 0 if not. Thus, $\boldsymbol{\lambda} = (\boldsymbol{\lambda}_1, \boldsymbol{\lambda}_2, \boldsymbol{\lambda}_3, \ldots, \boldsymbol{\lambda}_n)$ would be the vector representing the state of n people in the sampled population toward wildlife at a localized scale. When $\boldsymbol{\alpha}_i = 1$, $\boldsymbol{\lambda}_i$ follows a Bernoulli distribution and can have a value of 0 or 1 with conditional probability (φ). We assumed that when $\boldsymbol{\alpha}_i = 0$, $\boldsymbol{\lambda}_i = 0$. In other words, when people did not have a positive attitude toward wildlife notionally, they could not have a positive attitude toward wildlife in their neighborhood.

A commonly used structure of questionnaire surveys is multiple statements provided to respondents that the respondents either agree or disagree with (e.g., Røskaft et al. 2007; Bruskotter et al. 2009). We used a similar approach to assess attitudes of n respondents. Let there be J questions that relate to attitudes toward wildlife notionally and K questions that relate to attitudes toward wildlife at a local scale. The J questions then speak to respondents' notional attitudes ($\boldsymbol{\alpha}$), and the K questions speak respondents' local attitudes ($\boldsymbol{\lambda}$).

Responses of the sampled population to the above questions can be recorded in the form of a binary matrix, where an entry of 1 denotes a response aligned with a positive attitude toward wildlife and an entry of 0 denotes a response aligned with a nonpositive attitude toward wildlife. Simple measures, such as the average score or proportion of respondents reporting positive responses, have been used previously to quantify attitudes of people toward wildlife (Kansky et al. 2014). However, these measures do not account for biases arising from false reporting of a person's attitude toward wildlife; that is, the response of a person to a survey may not accurately reflect $\boldsymbol{\alpha}$ and $\boldsymbol{\lambda}$. We therefore considered the attitude states of respondents $\boldsymbol{\alpha}$ and $\boldsymbol{\lambda}$ as latent states.

As mentioned above, there are 2 forms of reporting error. False-negative errors occur when a respondent who has a positive attitude toward wildlife offers a nonpositive response to survey questions. False-positive errors occur when a respondent who has a nonpositive attitude toward wildlife offers a positive response to survey questions.

We borrowed from hierarchical approaches applied to address ecological questions (Williams et al. 2002; Royle & Dorazio 2008), in particular, those described as the "multiple detection method" by Miller et al. (2011). This approach allowed us to account for both false negative and false positive reporting while assessing notional and local-scale attitudes. The multidetection method requires there be at least 1 question subject to only 1 form of false reporting. That is, at least 1 question had to be subject to either only false-positive reporting or only false-negative reporting (hereafter, a certain [in the sense of *definite*] question [c]). We considered certain questions that were only subject to false-negative reporting error. The rest of the questions may be prone to false-positive and false-negative reporting (hereafter, uncertain questions [uc]). We used J_c and K_c certain questions and $J_{uc} = J - J_c$ and $K_{uc} = K - K_c$ uncertain questions to assess notional and local-scale attitude states of respondents, respectively.

We used p_c^{11} and q_c^{11} to denote the respective probabilities of true positive reporting for the *certain* questions when the respondents' true state was actually positive towards wildlife notionally and locally. The probabilities of false negative reporting for the certain questions notionally and at local scales therefore are $1 - p_c^{11}$ and $1 - q_c^{11}$, respectively. Similarly, we used p_{uc}^{11} and q_{uc}^{11} as the probabilities of true positives for the uncertain questions. We used p_{uc}^{01} and $q^{01}{}_{uc}$ to denote the probabilities of false positive reporting for the uncertain questions, notionally and at the local scale, respectively. By design, $p_c^{01} = q_c^{01} = 0$ (i.e., probability of false-positive reporting for certain questions was 0).

Let $\mathbf{X}$ (combining $\mathbf{X}_c$ and $\mathbf{X}_{uc}$) be the matrix of responses to the J_c and J_{uc} certain and uncertain questions on notional attitudes, respectively. The matrix $\mathbf{X}$ consists of n vectors $\mathbf{x}_i = (\mathbf{x}_{i1}, \mathbf{x}_{i2}, \mathbf{x}_{i3}, \ldots, \mathbf{x}_{ij})$, each recording $J = J_c + J_{uc}$ responses of each individual respondent i to survey questions. Similarly, $\mathbf{Z}$ (combining $\mathbf{Z}_c$ and $\mathbf{Z}_{uc}$) is the matrix of responses to certain and uncertain local-scale questions K_c and K_{uc}, respectively. The matrix $\mathbf{Z}$ consists of n vectors $\mathbf{z}_i = (\mathbf{z}_{i1}, \mathbf{z}_{i2}, \mathbf{z}_{i3}, \ldots, \mathbf{z}_{ik})$, each recording $K = K_c + K_{uc}$ responses of each individual respondent i. Together, these comprise the totality of responses $\mathbf{Y}$, a binary matrix of dimensions $n \times (J + K)$, in which elements can be 1 (response aligning to a positive attitude toward wildlife) or 0 (response aligning to a nonpositive attitude toward wildlife). Each set of responses is therefore an outcome of a binomial distribution, conditional on the latent state of the respondent and reporting error rates (Supporting Information).

We assumed the notional and local-scale attitude state of a respondent toward wildlife did not change during the course of the survey. Thus, if a respondent was positive toward wildlife notionally at the beginning of the survey, they remained positive until they finished providing responses for the survey. We also assumed that given the respondent's attitude and reporting errors, responses to questions were independent, which is possible due to the varied phrasing of questions (list of questions in Supporting Information).

The number of rows in matrices $\mathbf{X}_c$ and $\mathbf{Z}_c$ that had at least 1 record of a positive response was the naïve estimate of a positive attitude toward wildlife, notionally and at the local scale, respectively, which is equivalent to the proportion of respondents reporting a positive attitude toward wildlife.

Estimating the parameters ψ and φ (i.e., the probability of a person being positive toward wildlife notionally, and given such a positive attitude, being positive toward wildlife at the local scale, respectively) is important. However, there may be variation in these parameters across individuals, and identifying drivers of such variation is of interest both for conservation programs and to enhance overall understanding of attitudes. These drivers can be modeled using a probit link function (Supporting Information). Similarly, one can model the probabilities of false-positive and false-negative reporting as functions of both respondent-specific and question-specific covariates with a probit link.

We used Bayesian Markov chain Monte Carlo (MCMC) simulations with a Metropolis-Hastings algorithm (Supporting Information) to estimate parameters. We used a chain length of 20,000 iterations and a burn-in length of 5000 steps. Our analyses were composed of 2 parts. First, we measured bias in estimation of preset true parameter values with simulations. We then applied the model to real data. We used a single chain for the simulation study and 2 chains for the example application (details below). We used the maximum likelihood estimate of parameters as initial starting values. All analyses were carried out in R (R Development Core Team 2017) with libraries detailed in the Supporting Information, and RStudio (RStudio Team 2015).

Simulations

Forms of the hierarchical model we used have been extensively assessed elsewhere through simulations. For instance, MacKenzie et al. (2002) assessed the ability of hierarchical models to reliably estimate the system state parameter at multiple false-negative error rates. Gu and Swihart (2004) assessed reliability of inference obtained from these models on factors shaping the system state given non-0 false-negative error rates. Miller et al. (2011) show that hierarchical models can be used to reliably assess system state, given non-0 false-positive and false-negative error rates. Thus, we restricted our simulations to a comparison of the utility of the Bayesian hierarchical model, and commonly used measures to quantify people's attitudes toward wildlife.

We ran 2 sets of simulations. In the first set, we tested the model against a range of true (notional and local) attitude states. In the second set, we considered 4 scenarios that represented different degrees of reporting error, setting the probabilities of positive notional and conditional local attitudes to 0.6 (Supporting Information). We estimated the proportion of respondents who had positive attitudes toward wildlife and the probabilities of having positive attitudes toward wildlife with a Bayesian hierarchical model. We quantified the naive estimate of positive attitudes in the sampled population as the proportion of respondents who reported positive attitudes toward wildlife in at least 1 certain question. We also calculated scaled Likert scores for respondents derived from all questions. All of the above were evaluated at the notional level; at the local scale, irrespective of the respondent's notional attitude; and the local scale conditional on a positive notional attitude. We compared these estimated parameters with the preset true probability of respondents having a positive attitude toward wildlife notionally, at local scales conditional on a positive notional attitude, and at local scales independent of notional attitudes.

Attitudes toward Asian elephants

The Kaziranga–Karbi Anglong Elephant Reserve is a unique floodplain ecosystem with grasslands and forests separated by agricultural lands and tea estates. This landscape is arguably one of the most viable for the Asian elephant in the region. The tea estates, being part of the larger landscape, can serve as movement conduits and secondary habitat. However, elephant presence in the estates can be a source for conflict.

From 2015 to 2017, we conducted a questionnaire survey across 17 tea estates in this landscape. The survey has been approved by our institutional Human Subjects Committee and complied with their ethical guidelines. We used data from 2252 respondents from the 17 tea estates (1197 men [53%]; 1055 women [47%]). Respondents included 61 members of the management, 123 labor-union members, and 2068 laborers. The skewed representation is due to the significantly fewer managers compared with laborers in tea estates of the region. Respondents were chosen opportunistically. The surveys were in the form of statements about elephants that the respondent either agreed or disagreed with (Supporting Information). Responses were scored as either positive (1) or nonpositive (0) toward elephants. Data were collected as part of a larger survey and conservation program aimed at enhancing the conservation role of tea estates in the landscape. Our objective was to examine the applicability of the Bayesian hierarchical model to a real data set; hence, we did not explore in detail drivers of attitudes and false reporting. However, we did model the probability of a positive local attitude by tea estate identity.

To parse reporting error from the true latent attitude states, our hierarchical approach required the use of at least 1 certain question. We structured the certain questions so that only false-negative errors were possible, but the model could easily be modified such that the certain questions would be subject to only false-positive errors. The uncertain questions are subject to both false-positive and false-negative errors. In a practical sense, the decision of what constitutes a certain question comes from knowledge of the local socioecological context.

In the context of human–elephant interactions in the Kaziranga–Karbi Anglong landscape, we expected that a cultural linkage with elephants and an expectation of reverence of the animal would predominantly drive false-positive errors. We also expected that an expectation of compensation for crop loss would be a primary cause for false-negative reporting. Our certain notional question related to the statement, "Elephants are important because they keep the forests healthy," did not pertain to cultural or traditional links of people with elephants and did not conform with commonly held local opinions on elephant–forest relationships. Similarly, our local-scale certain question related to the statement, "Elephants deny us our crops," is a reality that respondents either face directly or have witnessed, and it is extremely unlikely they would deny this statement if their true attitude was nonpositive toward elephants. Therefore, these questions were viable choices.

We ran 2 Bayesian MCMC chains of 20,000 steps each, with a burn-in of 5000 steps. We used a thinning interval of 4 to obtain posterior distributions and credible intervals on estimated parameters. We assessed model convergence visually and with the Gelman–Rubin convergence diagnostic $\hat{R}$ (Gelman & Rubin 1992).

Results

Simulations

The Bayesian hierarchical modeling approach provided unbiased estimates of attitude states, albeit less precise under conditions of high reporting error (Figs. 1–4). This result held true for both sets of simulations: the first being across a range of preset true parameters for attitude state and reporting error rates (Fig. 1) and the second being with fixed preset true attitude states under 4 scenarios of reporting error rates (Figs. 2–4). Naïve estimates of the proportion of people showing positive notional and local attitudes were closer to the predetermined true values than scaled Likert scores, but were negatively biased; that is, they underreported the proportion of people with positive attitudes toward wildlife (Figs. 1–4). Likert scores were generally unreliable in estimating local attitudes toward wildlife (Figs. 1–4); from our analyses, they had a small range of variation that was unrelated to true parameter values. Precision (but not bias) of Bayesian MCMC estimates decreased as levels of false-negative reporting error increased (Figs. 2–4).

Attitudes Toward Asian Elephants

The estimated probability of a respondent having a positive notional attitude was 0.85 (95% credible interval

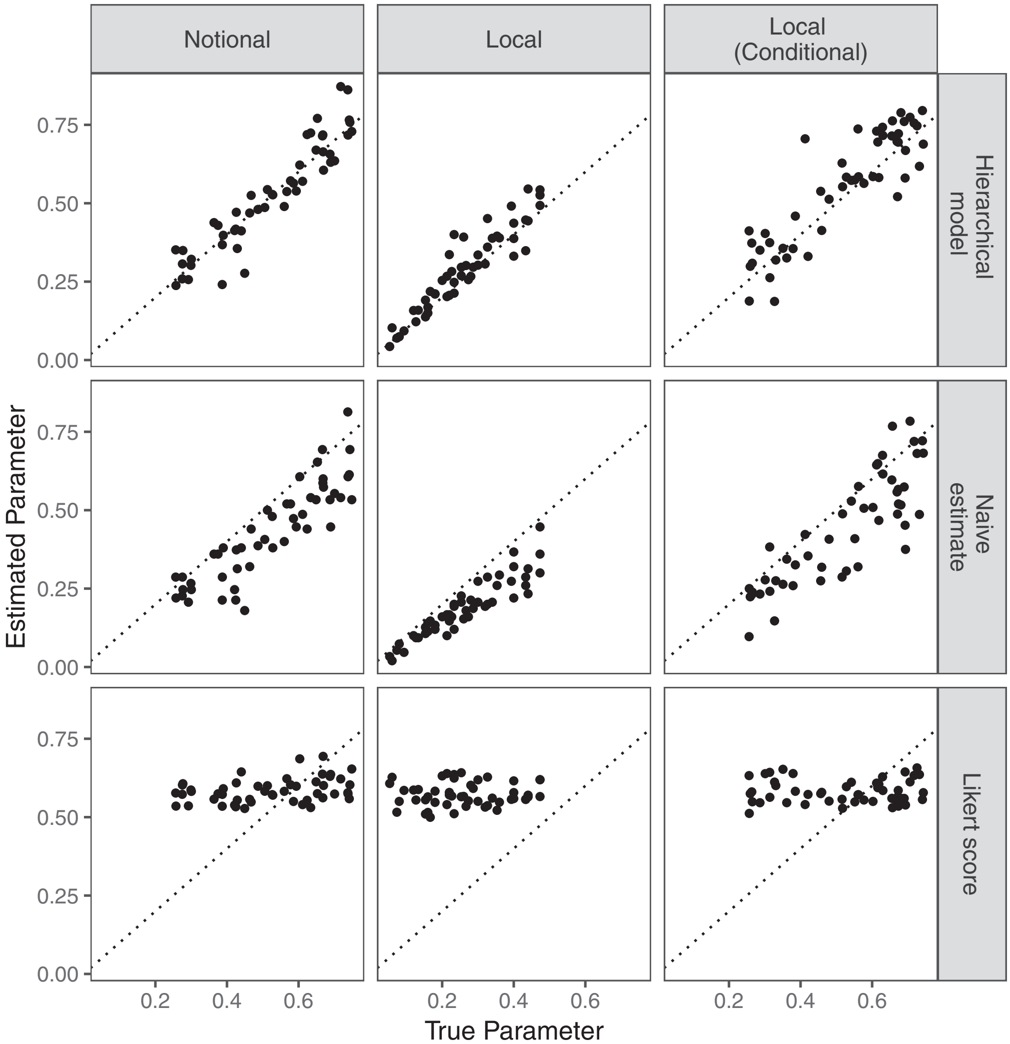

Figure 1. Relationship between the estimated and preset true parameter describing probability of having positive notional (i.e., in abstract terms) and local-scale attitudes toward wildlife for 3 approaches to attitude assessment: Bayesian hierarchical model that accounts for reporting error; naïve estimates or the proportion of respondents reporting a positive attitude toward wildlife for at least 1 certain question (i.e., questions with no chance of a false-positive response); and scaled Likert score of respondents (dotted line, expected relationship between an unbiased estimator and the true parameter value).

[CrI], 0.80–0.91). In comparison, 69% of respondents reported a positive notional attitude to wildlife in response to at least 1 of the certain questions (i.e., the naïve estimate), and 99% of respondents (2251 of 2252) reported a positive attitude in response to at least 1 question (*certain* or *uncertain*). Given a positive notional attitude, the probability of respondents having a positive local attitude varied by tea estate, ranging from 0.34 (95% CrI, 0.25–0.45) to 0.80 (95% CrI, 0.60–0.93). At a localized scale, the proportion of respondents who had a positive attitude (tracked by the latent state λ) was 0.50 across all tea estates (95% CrI, 0.36–0.59). This was higher than the naïve estimate of the proportion of respondents showing positive local-scale attitudes (0.23).

False reporting rates ranged from 0.22 (95% CrI, 0.22–0.23) for false-negative reporting of notional attitudes for uncertain questions to 0.68 (95% CrI, 0.65–0.72) for false-positive reporting of notional attitudes for uncertain questions. We report untransformed estimates, 95% CrIs, and the Gelman–Rubin convergence diagnostic $\hat{R}$ of estimated parameters in Table 1 and Supporting Information.

Discussion

We demonstrated, through our simulations and a practical example, that hierarchical models can be a useful approach to assessing people's attitudes while accounting for bias arising due to false reporting. The

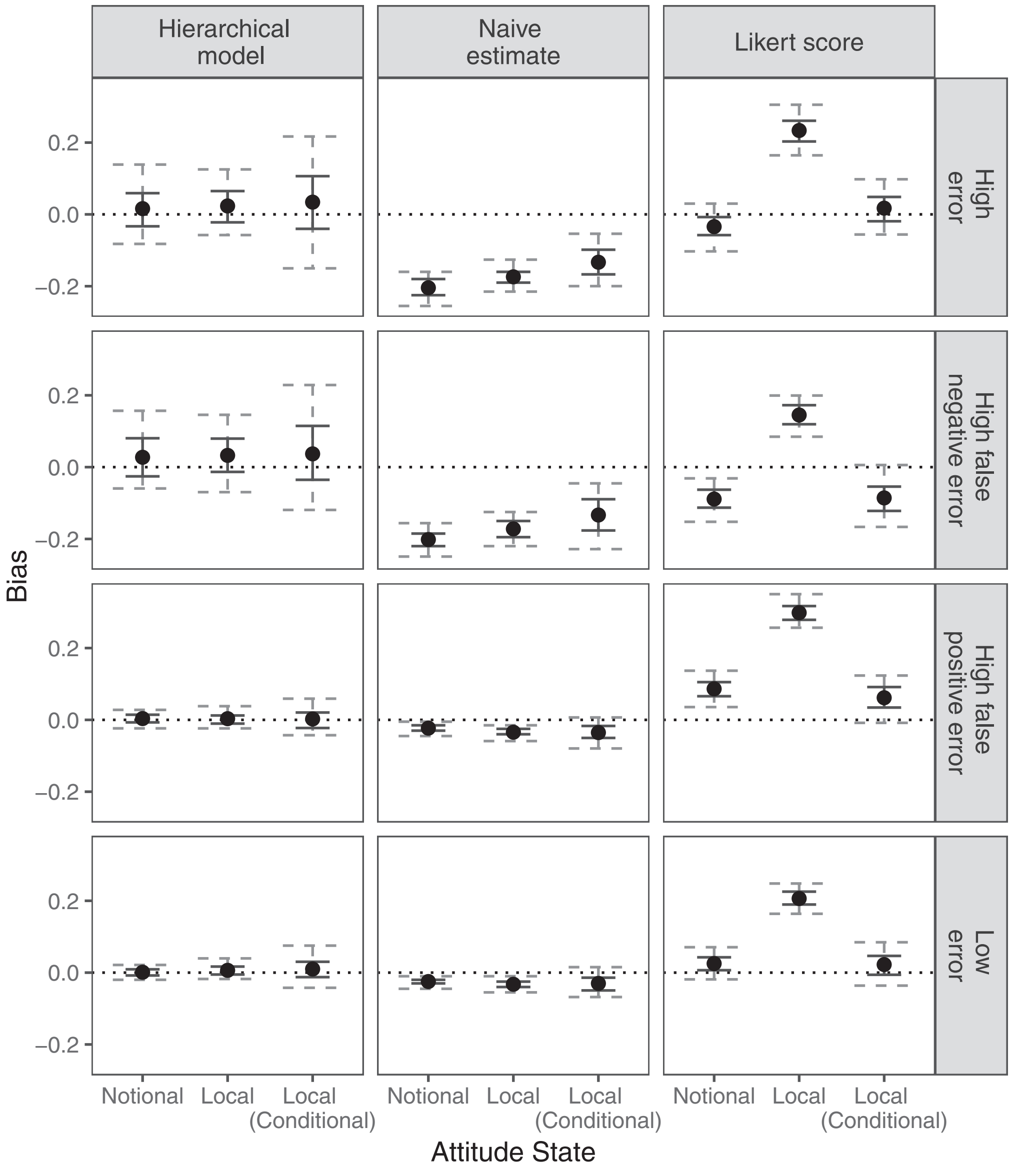

Figure 2. Bias (estimated value − true value) in estimated attitudes toward wildlife notionally (or in abstract terms), at a local scale unconditionally, and at a local scale conditional on being positive notionally and across 4 scenarios of false reporting rates based on 3 approaches to attitude assessment: Bayesian hierarchical model that accounts for reporting error; naïve estimate or the proportion of respondents reporting a positive attitude toward wildlife for at least 1 certain (i.e., questions with no chance of a false-positive response) question; and scaled Likert score (black dots, estimated value averaged across simulations; black error bars, estimates from 50% of simulations; gray error bars, estimates from 95% of simulations; dotted lines, 0 bias).

hierarchical model provided unbiased estimates of attitude states relative to naïve estimates or Likert scores in our simulations. In the practical application of the method, there was a substantial difference between naïve estimates and estimates obtained from the hierarchical model. A reliable assessment of stakeholder attitudes is undoubtedly important for many conservation programs globally. However, our findings highlight biases in inference on stakeholder attitudes from frequently used approaches.

Hierarchical models have been extensively used in the field of applied conservation research to parse processes of interest (here, attitudes of respondents) from observational processes (in our case, misreporting) (Williams et al. 2002; Royle & Dorazio 2008; Lachish et al. 2012; Goswami et al. 2015). These models have been used previously on data obtained from questionnaire surveys as well, accounting simultaneously for probabilities of false-positive and false-negative reporting (e.g., Pillay et al. 2014). Indeed, the use of hierarchical models in ecology

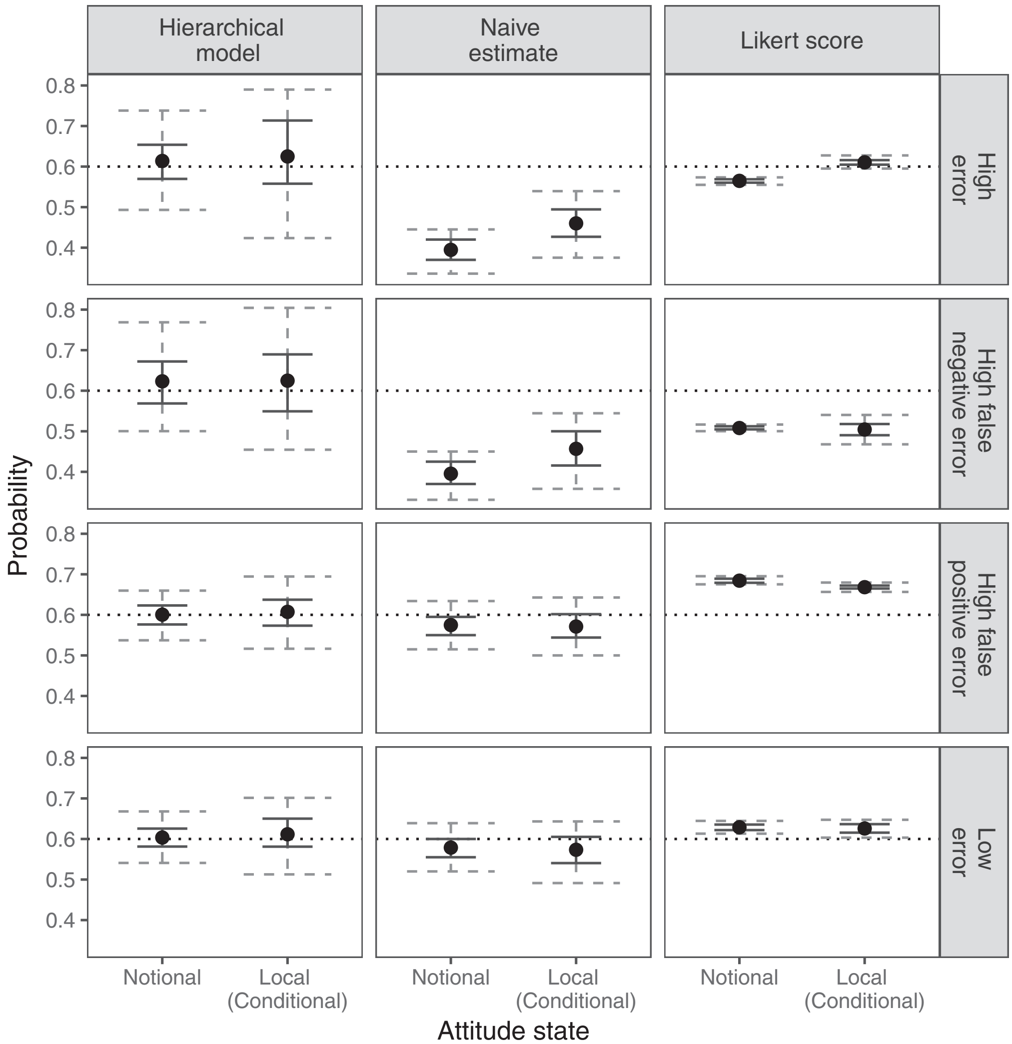

Figure 3. Estimated probability of a positive notional attitude and positive local attitude conditional on a positive notional attitude based on 3 approaches to attitude assessment (Bayesian hierarchical model that accounts for reporting error; naïve estimate or the proportion of respondents reporting a positive attitude toward wildlife for at least 1 certain question [i.e., questions with no chance of a false-positive response]; and scaled Likert scores) for 4 scenarios of false reporting error rates (black dots, estimated value averaged across simulations; black error bars, estimates from 50% of simulations; gray error bars, estimates from 95% of simulations; dotted lines, preset true parameter value [i.e., 0.6]).

and conservation science is well established (Williams et al. 2002; Royle & Dorazio 2008). The novelty of our approach lies in, first, the application of the method to reliably assess attitudes of people toward wildlife, which can be extended to attitudes towards nature, ecosystems, and conservation interventions, and, second, in that we extended the approach to explicitly separate notional attitudes from localized attitudes toward wildlife in a hierarchical (and thus conditional) manner.

At the outset, we note that people's attitudes may often be more complicated than what can be encompassed within a binary measure. Hence there may be a loss of information when people's attitudes are classified only as positive or nonpositive. A more detailed assessment of people's responses to a multitude of questions, data that are available within the framework of this approach, could provide additional nuanced insights into the complexities of human–nature relationships that the analytical approach described here is not designed to capture. Nonetheless, there is interest and need to quantify people's attitudes toward wildlife (e.g., Sterling et al. 2017). Multiple approaches to assessing attitudes, with data obtained under the same study design, could be complementary and collectively of much utility for conservation.

There are at least 3 reasons to quantify stakeholder attitudes. First, with recognition of the importance of stakeholder support for conservation success (Bennett et al. 2017), monitoring of stakeholder attitudes in

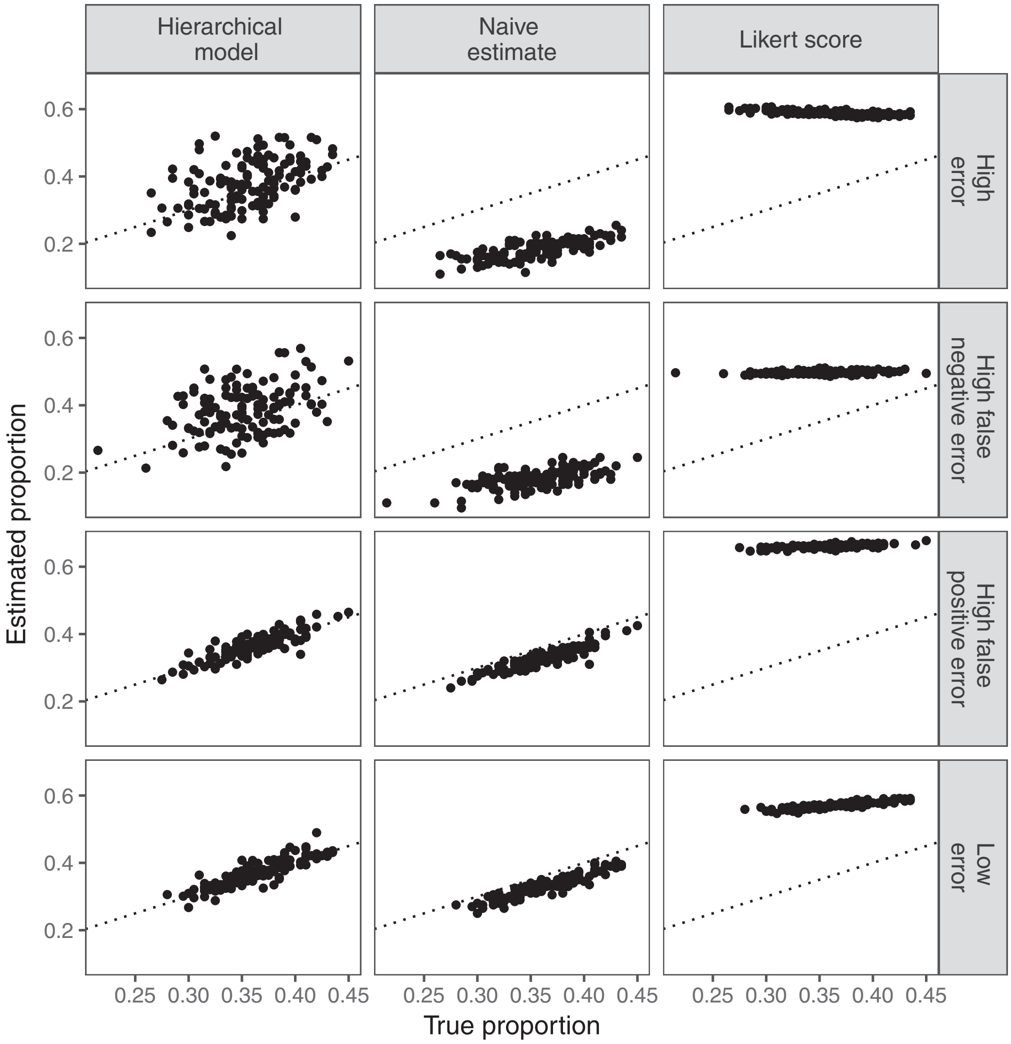

Figure 4. Estimated proportion of respondents with a positive local attitude relative to the true proportion of respondents with a positive local attitude for each simulation under 4 scenarios of reporting error (dotted line, expected relationship between an unbiased estimator and the true value).

conservation landscapes has become increasingly critical. Second, success of conservation interventions aimed at improving stakeholder attitudes (e.g., stakeholder engagement meetings, awareness programs, conservation messaging) can only be assessed through the quantification of attitudes (Sterling et al. 2017). Third, insights into drivers of positive (or nonpositive) attitudes toward wildlife, through quantitative assessment (e.g., Kansky et al. 2014), are important to understanding behavioral change of stakeholders. Yet there are few examples of quantitative monitoring of people's attitudes toward wildlife in a manner that accounts for reporting error. Our data showed that rates of false reporting were non-0 and hence non-negligible (0.22–0.68 in our case study) (Table 1). We believe our proposed hierarchical modeling approach can fill this gap.

We estimated relatively high levels of false-positive errors in our landscape (Table 1). In general, there may be multiple reasons for (intentional or subconscious) false reporting (Fisher 1993; Nuno & St. John 2015) (Fig. 5). False-positive or -negative errors can come from the respondent's instinct to conform with their perception of surveyors' beliefs (Fisher 1993). The instinct to conform to socially acceptable behavior can lead the respondent to align their response with cultural or traditional norms (Fisher 1993). There may similarly be an expectation, or peer pressure, to retain such norms, even when changing sociocultural and socioeconomic circumstances lead individuals towards socially undesirable beliefs. An instinct to concur with what respondents believe is the majority opinion (Koriat et al. 2018) can lead to either false-positive responses—when they believe the majority hold the species or nature in reverence—or false-negative responses. The latter can arise due to perceived community concerns pertaining to losses or safety risk from certain wildlife species. In our landscape, for instance,

Table 1. Untransformed parameter estimates, 95% credible intervals (CrI) and the Gelman–Rubin convergence diagnostic $\hat{R}$ for each estimated parameter in our model for assessing attitudes of people toward elephants in the Kaziranga–Karbi Anglong landscape.[a]

Parameter[b]	*Estimate (95% CrI)*	*Gelman–Rubin* $\hat{R}$
ψ	1.701 (1.400–2.301)	1.01
φ (intercept)	−0.243 (−0.725–0.309)	1.01
φ (tea estates)	−0.401 (–1.068–0.188) to 1.816 (0.819–2.887)	1.00 – 1.01
p_{c}^{11}	0.796 (0.684–0.908)	1.01
p_{uc}^{11}	1.244 (1.206–1.281)	1.00
p_{uc}^{01}	0.773 (0.600–0.949)	1.00
q_{c}^{11}	0.105 (−0.142–0.639)	1.07
q_{uc}^{11}	0.305 (0.253–0.400)	1.02
q_{uc}^{01}	0.032 (0.004–0.061)	1.00

[a] *We modeled the probability of positive local attitude (φ) as a function of tea estate. We provide the intercept and range of estimated coefficients here. Individual tea estate coefficients are provided in Supporting Information.*

[b] *Variables: ψ, probability of a respondent having a positive attitude notionally; φ, probability of a respondent having a positive localized attitude; conditional on a positive notional attitude p_{c}^{11}, probability of positive reporting, given positive attitude for certain questions (i.e., questions with no chance of a false-positive response) on notional attitudes; p_{uc}^{11}, probability of positive reporting, given positive attitude, for uncertain questions on notional attitudes; p_{uc}^{01}, probability of positive reporting, given nonpositive attitude, for uncertain questions on notional attitudes; q_{c}^{11}, probability of positive reporting, given positive attitude, for certain questions on localized attitudes; q_{uc}^{11}, probability of positive reporting, given positive attitude, for uncertain questions on localized attitudes; q_{uc}^{01}, probability of positive reporting, given nonpositive attitude, for uncertain questions on localized attitudes.*

87% of respondents directly faced or knew of someone who had faced crop loss to elephants, and 39% had faced or knew someone who had faced injury from elephants. False-negative responses can also arise from expected community concerns over potential restrictions that may be imposed due to conservation actions (McClanahan et al. 2005).

The naïve estimate of people's attitudes performed reasonably well in our simulations in terms of estimating true parameter values. Restricting inference to the naïve estimate, however, would still entail misleading inference on drivers of positive attitudes and by extension, human behavioral change (Gu & Swihart 2004). Drivers of false reporting could also be of interest to conservation scientists, and our method is amenable to such an assessment. Further, we restricted our calculation of the naïve estimate to certain questions. This, and the misalignment of Likert scores (averaged across all questions) to our model estimates, suggest that inclusion of a few questions that limit bias to that arising from one form of reporting error is more useful than increasing the number of questions to include those vulnerable to both false-positive and false-negative reporting error.

In our landscape, the probability of a person having a positive attitude toward wildlife notionally was significantly different from local-scale attitudes, which were specifically tied to the respondents' belongings, lands, or livelihood. It is likely that the same patterns may

True attitude state	Response	
	Positive	Nonpositive
Positive	*True positive response*	*False negative response* Expectation of remuneration or compensation Maintaining consonance with expected community concerns vis-à-vis loss or safety risk from the species Maintaining consonance with expected community concerns of potential restrictions from conservation actions Alignment of response with the overall goal of the surveyor
Nonpositive	*False positive response* Maintaining consonance with an expected majority response when people have cultural ties with the species or nature Social expectation of positive response due to traditional or cultural norms Alignment of response with the overall goal of the surveyor	*True nonpositive response*

Figure 5. A schematic representation of potential drivers of reporting error.

be evident in other landscapes. Kansky et al. (2014), in a review of people's attitudes toward conflict-prone mammals, found that attitudes were highly dependent on the type of question. Questions, although not explicitly stated as such in their review, differed in whether they addressed localized or notional attitudes. Inferring positive notional attitudes as indicative of positive localized attitudes could lead to an overoptimistic assumption of tolerance, which could impede conservation. In our landscape, for instance, the probability of a person having a positive attitude toward wildlife declined by 40% when moving from notional perspectives to a localized scale. Local-scale attitudes, it can be argued, are most pertinent to conservation. Further, it can be expected that drivers of positive notional attitudes may be different from those at localized scales. However, assessments of attitudes sometimes combine questions that relate to notional perspectives and questions pertaining to localized scales and do not always segregate them in analyses or inference (e.g., Bruskotter et al. 2009). Explicit recognition of the level at which attitudes are being assessed (i.e., whether they pertain to notional attitudes or those at local scales) could allow further insight into attitudes and seamless cross-comparisons among studies.

In light of increasingly integrated human–natural systems and conservation in heterogeneous landscapes with an extensive human–wildlife interface, stakeholder attitudes, and consequent responses to wildlife and conservation initiatives are highly relevant. The approach described here can be used to reliably quantify people's attitudes toward wildlife and conservation, while accounting for biases arising from false-positive and false-negative reporting. Given the wide applicability of the approach to reliably evaluating stakeholder attitudes, we expect it to be of substantial value to conservation practice. Further, with this approach, it is very feasible to quantitatively evaluate stakeholder attitudes as a function of various underlying factors. Insights into drivers of attitudes, as well as factors that shape rates of false reporting, can greatly enhance the understanding of why people respond to wildlife species and conservation interventions in a particular manner. In turn, such understanding will allow the tailoring of strategies aimed at achieving human behavioral change for maximum conservation effectiveness.

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Supporting Information

A definition of parameters used (Appendix S1), the binomial distributions that generated data (Appendix S2), description of simulations (Appendix S3), R libraries (Appendix S4), list of survey questions (Appendix S5), description of the hierarchical model (Appendix S6), formulation for Likert scores (Appendix S7), MCMC chains (Appendix S8), and untransformed estimates from the practical example (Appendix S9) are available online. 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. Data and script used in the example application are available from Dryad (DOI: 10.5061/dryad.03g98h6).

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