Received: 31 March 2025 | Accepted: 29 April 2025
DOI: 10.1002/pan3.70085

RESEARCH ARTICLE

Socio-ecological correlates of wildlife species identification across rural communities in northern Tanzania

Justin Raycraft[1] | Reilly Becchina[2] | Danielle Bettermann[3,4] | Stephen Koester[5] | Elana Kriegel[6,7] | Kiana Lindsay[8,9] | Edwin Maingo Ole[10] | Emily Ramirez[11] | Bryan Spizuco[12] | Christian Kiffner[13,14,15]

[1]Department of Anthropology, University of Lethbridge, Lethbridge, Alberta, Canada; [2]Department of Anthropology, University of Maryland, College Park, Maryland, USA; [3]Department of Environmental Initiative, Lehigh University, Bethlehem, Pennsylvania, USA; [4]Department of History and Philosophy, University of Münster, Münster, Germany; [5]Muhlenberg College, Allentown, Pennsylvania, USA; [6]Department of Animal Science, Cornell University, Ithaca, New York, USA; [7]Albany Medical College, Albany, New York, USA; [8]University of San Diego, San Diego, California, USA; [9]School for Environment and Sustainability, University of Michigan, Ann Arbor, Michigan, USA; [10]Department of Agricultural Extension and Community Development, Sokoine University of Agriculture, Morogoro, Tanzania; [11]Lafayette College, Easton, Pennsylvania, USA; [12]The Rochester Institute of Technology, Rochester, New York, USA; [13]Division of Land Use Systems, Albrecht Daniel Thaer-Institute of Agricultural and Horticultural Sciences, Humboldt-Universität zu Berlin, Berlin, Germany; [14]Center for Wildlife Management Studies, School for Field Studies, Karatu, Tanzania and [15]Leibniz Centre for Agricultural Landscape Research (ZALF), Müncheberg, Germany

Correspondence
Christian Kiffner
Email: christian.kiffner@hu-berlin.de

Funding information
The Canadian Anthropology Society; Social Sciences and Humanities Research Council of Canada (SSHRC); Prentice Institute for Global Population and Economy; University of Lethbridge; Directed Research Fund of the School for Field Studies

Handling Editor: Catriona MacLeod

Abstract

1. Citizen or community science has the potential to inform wildlife management by including the general public in research and generating datasets on human perceptions of wildlife population dynamics and human–wildlife interactions. These contributions are especially valuable in areas with limited formal capacity for wildlife monitoring.
2. However, people's perceptions are not always reliable and hinge on the accurate classification of species. In the absence of artificial intelligence-supported automatic identification tools or wildlife experts, effectively incorporating people's reports of wildlife sightings into conservation management plans depends on the abilities of people to accurately identify animals (i.e. species literacy). These skills likely vary across human populations in accordance with a range of demographic, geographic and species-specific factors.
3. We carried out 680 semi-structured interviews with rural citizens, randomly selected along transects in 25 villages across northern Tanzania. We showed photographs of 17 mammal species to participants and assessed species identification ability. Using a generalized linear mixed model within a Bayesian framework that accommodated the hierarchical data structure and non-independence of the data, we tested specific hypotheses regarding the correlations of species identification accuracy with human demographic (ethnicity, education, age, wealth, gender), geographic (Human Footprint Index

This is an open access article under the terms of the Creative Commons Attribution License, which permits use, distribution and reproduction in any medium, provided the original work is properly cited.
© 2025 The Author(s). *People and Nature* published by John Wiley & Sons Ltd on behalf of British Ecological Society.

[HFI], distance to protected areas, district) and species-specific (conservation status, activity patterns, body mass, diet) variables.

4. Most respondents accurately identified key wildlife species commonly involved in human–wildlife interactions. Gender strongly influenced species identification accuracy, with men three times more likely to correctly identify species as compared to women. Formal education was negatively correlated with species identification accuracy.
5. Respondents identified large species more accurately than smaller ones, whereas other species traits were not markedly correlated with identification accuracy. Distance to the nearest protected area, district and the HFI score in the area surrounding the household of the respondent were not markedly associated with species identification accuracy.
6. Our results show that rural residents in northern Tanzania can reliably identify key wildlife species implicated in consequential human–wildlife interactions, though identification accuracy was affected by a combination of demographic and species-specific factors that must be appropriately contextualized. This finding validates studies of local perceptions of wildlife populations and community reports of human–wildlife interactions. Finally, we discuss how local perspectives on wildlife can be applied to improve human–wildlife coexistence.

KEYWORDS
citizen science, human–wildlife coexistence, human–wildlife conflict, human–wildlife interactions, large carnivores, large herbivores, local ecological knowledge, species literacy

1 | INTRODUCTION

In recent years, citizen science (or community science)—participation in research by the general public regardless of formal scientific training—has gained traction as a means of gathering information on wildlife populations, especially in remote areas where professional capacity is limited (Backstrom et al., 2024).[1] However, the inclusion of and reliance on data generated by laypeople has prompted questions about the quality of these diverse and varied sources of knowledge (Abra et al., 2018; Crall et al., 2011; Eisen & Eisen, 2021; Gilchrist et al., 2005; Johnston et al., 2023; Lukyanenko et al., 2016; Pierotti & Wildcat, 2000; Ratnieks et al., 2016). While citizen science can offer useful insights into human–wildlife encounters (see Teel et al., 2022), the variability in laypeople's abilities to accurately identify species undermines the potential contributions of these forms of knowledge to formal scientific discourse (Gorleri & Areta, 2022). Consensus from existing studies seems to be that data on human perceptions of wildlife dynamics are potentially valuable to conservation science, however, in the absence of AI-supported automatic identification tools (cf. Truong & Van der Wal, 2024), triangulation by the international scientific community via digital platforms like iNaturalist (Callaghan et al., 2022), or quantitative methods for verifying the accuracy of people's claims (Binley & Bennett, 2023), they should be interpreted and applied cautiously (Aceves-Bueno et al., 2017; Gilchrist et al., 2005; Rowley et al., 2019).

One approach for assessing the accuracy of community science reports of wildlife dynamics is through the concept of 'species literacy', defined by Hooykaas et al. (2019) as general knowledge about wildlife species, evaluated through species identification tests and factors affecting correct identification (see also Hooykaas, 2022). We conceptualize species literacy as a particular aspect of local ecological knowledge (LEK), which refers to the beliefs, practices and understandings that are developed and shared by groups of people through intimate interaction with local ecosystems (Charnley et al., 2007; Joa et al., 2018; McQuaid, 2022). Depending on the cultural context, LEK is sometimes couched within broader frameworks of traditional Indigenous knowledge, referred to in some discourses as Traditional Ecological Knowledge (TEK), or the entire repository of knowledge that is adapted across generations through cultural practices and social institutions (Berkes et al., 2000; Ostertag et al., 2018). This paper focuses narrowly on the species literacy of rural communities in northern Tanzania, operationalized in terms of people's abilities to correctly identify wildlife species. Informed by anthropological scholarship on TEK, we broaden Hooykaas

[1] Citizen science is sometimes referred to as 'community-based monitoring', 'community science' or 'participatory science' (see Eisen & Eisen, 2021) as those titles are more inclusive. In this manuscript, we use the phrase citizen science as it is well-established terminology yet define it to be inclusive. In this case, our sample population comprised Tanzanian citizens.

et al.'s (2019, 2022) definition of species literacy to include different languages (*Maa* and *kiSwahili*), depending on the linguistic profiles of our respondents, thus tailoring the concept to apply in cross-cultural contexts. In East Africa, little is currently known about the extent to which rural communities can correctly identify wildlife species. While qualitative accounts exist, there has not been a systematic, quantitative assessment of the range of social and ecological factors affecting people's abilities to correctly identify wildlife species.

Our interest in carrying out a rigorous quantitative study of wildlife species identification abilities in this context aligns with Gilchrist et al. (2005) who advocate for the use of LEK in wildlife management, but caution against the application of human perception data without first ensuring the accuracy of people's observations. Similarly, Binley and Bennett (2023) suggest the use of statistical modelling to address potential biases and limitations of observational data from laypeople. In contexts where people's perceptions cannot be verified with AI-supported systems or wildlife experts, understanding the extent to which laypeople's species identification skills line up with those of wildlife professionals is crucial (Falk et al., 2019), especially in areas with frequent human–wildlife interactions (HWI). In northern Tanzania, where large mammals are not confined to protected areas, and spend prolonged periods on village lands, HWIs are not only frequent but also have severe impacts on human livelihoods, well-being and wildlife population persistence (Kiffner et al., 2022). The primary issues from a community livelihood perspective are livestock predation by carnivores and crop raiding by wild ungulates and elephants, but cases of property damage, human injury and death also occur (Bencin et al., 2016; Kissui et al., 2022; Raycraft, 2023, 2024b). HWI are regularly reported by local community members to government authorities, non-governmental organizations or researchers. Beyond incurring direct economic costs, which challenge food security, HWI also engender health impacts and indirect opportunity costs (Barua et al., 2013). Understanding patterns of HWI is a crucial first step for addressing this conservation conflict (Redpath et al., 2013). However, in some cases, wildlife professionals struggle to verify the claims put forth by communities and there is a paucity of studies evaluating the reliability of observational wildlife data generated by rural citizens. Establishing a baseline of rural citizens' abilities to identify common species of large mammals could offer important insight into the accuracy of HWI reports.

The association between species identification accuracy and in-depth species knowledge has generated considerable debate. Katswara and Mukaratirwa (2021) showed that livestock keepers in South Africa were able to correctly identify species of ticks, though their knowledge about tick ecology and the precise pathways for transmitting pathogens was limited. Similarly, Panisi et al. (2022) found that conservation attitudes did not correlate with species identification skills, suggesting that there is gap between species literacy and environmentalism. However, Hooykaas et al. (2022) concluded that species identification was 'by far the best predictor for in-depth knowledge about species' as compared to demographic variables ranging from employment, sex, age and education (Hooykaas et al., 2022: 1). These findings suggest that species identification tests are valuable, not only as indicators of the accuracy of local reports of wildlife sightings and community-based ecological monitoring regimes, but also as predictors of deeper forms of knowledge about wildlife.

Our study's emphasis on wildlife species identification abilities contributes to recent scholarship on the interface between citizen science and HWI research (Moussa & Mohan, 2024; Ostermann-Miyashita et al., 2021). Backstrom et al. (2024) make the case that observational data of wildlife collected by rural citizens have the potential to directly improve biodiversity monitoring in remote areas. These efforts have been bolstered over the past 20 years through the development of mobile software applications and the proliferation of digital photography (Vohland et al., 2021). Benefits of this approach have included the generation of unstructured and structured datasets through opportunistic sampling and have helped forge bidirectional pathways of communication between scientists and the general public (Pernat et al., 2025).

While citizen science projects have largely focused on helping to map the locations of particular taxa (Callaghan, Poore, Mesaglio, et al., 2021), or quantify the abundance of species (Callaghan, Nakagawa, et al., 2021), our applied interest here is mainly in using the primary accounts of people to understand the spatial and temporal distributions of HWIs on shared landscapes outside protected areas in northern Tanzania.[2] We are interested in understanding the potential for people's reports of wildlife to inform scientific understanding of local ecological dynamics. Existing citizen science studies have made applied contributions to freshwater monitoring (von Gönner et al., 2023), wildlife roadkill assessments (Pinto et al., 2024) and insect monitoring (Sheard et al., 2024) using digital software applications, though in our study villages such applications were not yet accessible to most people. We have thus focused our analysis here on the species identification skills of people living in rural northern Tanzania and the predictors of variability in these abilities.

Previous studies comparing species identification skills of laypeople and professionals have produced mixed results. Crall et al. (2011) found that wildlife identification skills of citizen volunteers were almost as accurate as professionals, though they cautioned that both groups faced concerns about data quality. They found that age, education, experience, scientific literacy and conservation attitudes did not predict wildlife species identification abilities among volunteers but noted that people's levels of comfort (i.e. their self-confidence) in identifying species correctly may have been influential. However, other studies exploring correlations between demographic variables and people's abilities to correctly identify wildlife species suggest that age (Huxham et al., 2006), gender (Corbett et al., 2005; Silva et al., 2022), education (Anđić et al., 2022; Hooykaas, 2022; Valliere, 2022) and wealth (Panisi et al., 2022) may be significant predictors of people's abilities to identify wildlife species.

[2]See Pernat et al. (2024) for discussion of primary and secondary citizen science data.

A range of other biological factors also likely play a role, as evidenced by differences between people's abilities to identify native and non-native wildlife species (Silva et al., 2022), and animals from different classes (Hooykaas et al., 2019; Huxham et al., 2006; see also Panisi et al., 2022). In particular, one may expect that more conspicuous mammals—such as large-bodied species, diurnal species that can be more easily observed compared to nocturnal species and species that are relevant to one's livelihood (e.g. large carnivores may pose a threat to pastoralists, whereas large herbivores may be more problematic for crop farmers)—are easier to identify by lay people than species that are difficult to detect or not directly relevant to their livelihood. Callaghan, Poore, Hofmann, et al. (2021), for instance, found that large-bodied birds were overrepresented in citizen science datasets from the iNaturalist platform, which they attributed to the greater ease of detecting and photographing large-bodied species.

Recent literature also suggests differences in wildlife species identification skills between urban and rural residents. For instance, Bashan et al. (2021) reported rural residents had better species identification abilities than urban residents, though their findings varied by species and were entangled with people's familiarity about the species and perceived levels of connectedness to nature. Panisi et al. (2022) also found positive effects of rurality on species identification. Similarly, Silva et al. (2022) reported that Brazilian male university students who regularly visited the countryside to farm, hunt and fish were better able to correctly identify native mammal species as compared to people who did not frequent rural areas. Though not directly investigating correlates of species identification ability, Ostermann-Miyashita et al. (2022) found that exposure to wildlife predicted people's levels of knowledge about wildlife. In this study, we use the Human Footprint Index (HFI)—which maps the relative influence of human land uses on terrestrial biomes—as a proxy measure of the urban–rural gradient and potential differences in species exposure.

Based on this review of literature and our understanding of the ecological and ethnographic context of the study, we organized our analysis into geographic variables, human demographic variables and species-specific variables (Table 1). We test these hypotheses using data from 680 household interviews conducted in northern Tanzania and assess how these variables affect the abilities of people to identify 17 common mammal species (Table 2). Based on our findings, we then discuss the potential applications of local perceptions and knowledge to wildlife management in our study area.

2 | MATERIALS AND METHODS

2.1 | Study area

We carried out this study in 25 villages spanning four districts (Karatu, Babati, Monduli and Kiteto) in northern Tanzania. Villages were selected purposively based on their proximity to a well-known network of national parks and community-based conservation areas (Figure 1) including: Makame Wildlife Management Area (MWMA), Randilen Wildlife Management Area (RWMA), Burunge Wildlife Management Area (BWMA), Manyara Ranch (MR), Tarangire National Park (TNP), Lake Manyara National Park (LMNP) and Ngorongoro Conservation Area (NCA). Since these conservation areas are unfenced and village lands partially represent suitable habitat for many wildlife species, wildlife occurrence on village lands is common (Bencin et al., 2016; Vallin et al., 2025). Bimodal rainfall patterns necessitate seasonal migration of zebra and wildebeest in the central part of the study area and less-regular movements of other wildlife species; some villages also host resident wildlife across seasons (Kiffner et al., 2016). The study area has a species-rich wildlife assemblage (see Table 2 for scientific species names), but the composition of large mammal communities differs regionally (Diplock et al., 2018).

Villages in our study area are inhabited by a diversity of ethnic groups. Those in Karatu district, in the northwestern portion of our study area, are populated predominantly by Iraqw people. Iraqw livelihood practices centre on subsistence crop cultivation of maize, beans and peas to make productive use of fertile highland soils (elevation between 1300 and 1700 m a.s.l.) and plentiful rainfall (1000 mm on average per year) (Prins & Loth, 1988). Savanna wildlife species like cheetah, impala, wildebeest, zebra and giraffe are not found in these village lands (Diplock et al., 2018), though the adjacent forest reserve within the NCA hosts numerous other large mammal species including elephant, buffalo, hyena, leopard and occasionally lion (Homewood & Rodgers, 2004; Kiffner et al., 2021).

Villages in the Monduli and Babati districts, in the central part of our study area, are situated within the greater Tarangire ecosystem. The ecosystem supports long-distance seasonal migration of wildebeest, zebra and other species outside TNP, as well as populations of resident wildlife (Gereta et al., 2004; Kiffner et al., 2016; Morrison & Bolger, 2012). Villages in Monduli and Babati range in elevation from 980 to 1200 m a.s.l. and encompass semi-arid landscapes that generally receive between 250 and 650 mm of rainfall per year (Prins & Loth, 1988). Most people living in these study villages self-identify as Kisongo Maasai or WaArusha. Both of these ethnic groups speak *Maa* and participate in an interconnected regional economy, though they are culturally distinct (Raycraft, 2022b). While farming has been increasing in this area (Msoffe et al., 2011), pastoralism is still the primary livelihood strategy. As such, livestock herd sizes were notably larger in Babati and Monduli as compared to those in Karatu (see Table S1). Our study villages in these districts were located between LMNP and TNP (Figure 1), in areas adjacent to BWMA, RWMA and MR.

Member villages of RWMA and BWMA participate in conservation management and receive a share of tourism revenue pursuant to the legal framework for wildlife management areas in Tanzania (Raycraft, 2022a; USAID, 2013; Wilfred, 2010). MR integrates pastoral livelihoods with wildlife conservation objectives by permitting seasonal grazing access for member villages (Kiffner et al., 2020). Kiteto district constitutes the southern part of the Tarangire ecosystem. We selected a member village of MWMA for this study, which was inhabited almost exclusively by Kisongo Maasai. Maasai in Kiteto uphold pastoral livelihoods including the maintenance of large herds and customary patterns of livestock grazing. MWMA's assemblage of large mammals is almost intact, other than rhinos

TABLE 1 Variables hypothesized to influence mammal species identification (ID) accuracy in northern Tanzania.

Variable category	General hypothesis	Specific predictions	Proxy used	References
Geographic variables	Urban–rural gradient mediates species ID accuracy	Those living in rural areas are more likely to accurately identify species as they are more exposed to these species	HFI (index ranging from 0 to 1)	Bashan et al. (2021); Panisi et al. (2022); Silva et al. (2022)
	Distance to protected area affects species ID accuracy	People living closer to protected areas more accurately identify species as they are more exposed to these species	Distance to closest protected area (in kilometres)	Ostermann-Miyashita et al. (2022)
	District mediates species ID accuracy	Community structure of wildlife species differs slightly across districts and these differences in exposure may mediate species ID accuracy	District (Babati, Monduli, Karatu, Kiteto)	Diplock et al. (2018)
Human demographic variables	Gender influences species ID accuracy	Men are more likely to accurately identify species than women as their main activities (e.g. herding livestock) may create greater exposure to wildlife	Gender category (man or woman)	Silva et al. (2022); Corbett et al. (2005)
	Age mediates species ID accuracy	Species ID accuracy increases with age or follows a hump-shaped correlation	Age (in years)	Huxham et al. (2006); Silva et al. (2022)
	Ethnicity affects species ID accuracy	Pastoral groups are more likely to accurately identify carnivores; cultivators are more likely to identify herbivores	Ethnic group (Maasai, Iraqw, WaArusha, Other)	
	Education affects species ID accuracy	Formal education is positively associated with species ID accuracy	Education level (none, primary, secondary and above)	Valliere (2022); Hooykaas (2022); Anđić et al. (2022)
	Livestock holdings mediate species ID accuracy	The size of the livestock herd is positively associated with species ID accuracy	Livestock owned by household (Tropical livestock units)	
	Land holdings mediate species ID accuracy	The size of farmland is positively associated with species ID accuracy	Area under cultivation (acres)	
Species-specific variables	Species daily activity patterns associated with species ID accuracy	Diurnal species are positively associated with species ID ability as people may be more exposed to diurnal species	Category of diurnal activity (diurnal, cathemeral and nocturnal)	
	Animal size affects species ID accuracy	Larger sized species are more accurately identified as they are more conspicuous	Body mass (in kg)	Callaghan et al. (2022)
	Feeding type affects species ID accuracy	Carnivores are more accurately identified than herbivores as interactions with these species may be perceived to have greater impact	Feeding type (Herbivore or carnivore)	
	Conservation status affects species ID accuracy	Least threatened species are more accurately identified as they are more frequently encountered	IUCN Red List categories (not threatened or threatened)	

(Baker et al., 2022). It generates revenue through carbon offset programs and trophy hunting blocks. Further information on the descriptive demographic statistics of our study participants can be found in Table S1.

2.2 | Sampling procedures and human demographic variables

Before commencing research, we submitted our research proposal for review to the Tanzania Commission for Science and Technology (COSTECH) and the Tanzania Wildlife Research Institute (permit numbers: 2016-349-NA-2013-191; 2017-288-ER-2013-191; 2019-92-NA-2103-191). Our study was subject to an internal ethical review by COSTECH and the School for Field Studies and we also received ethical approval from McGill University (REB File #: 479–0419) for the conduct of research with human subjects. Further permissions were provided in the form of written letters from regional and district governments, and oral clearances from village governments to carry out research at the local level. Surveys were carried out in 2017 (Karatu, Babati and northern Monduli), 2019 (Kiteto) and 2020 (eastern Monduli). In 2020, we followed all local research guidelines and ensured that COVID-prevention protocols were followed (i.e. social distancing, carrying out surveys outdoors).

TABLE 2 Characteristics of wildlife species, ordered by body mass. Data on body mass were gleaned from Clauss et al. (2021), Kiffner et al. (2015) and Wood et al. (2021); if species refer to two sister species, we used the average of the two body mass values. Classification of activity was based on Clauss et al. (2021) and Bennie et al. (2014). The IUCN variable was based on the corresponding species account and was condensed to 'Not threatened' (IUCN categories: 'Least concern' and 'Near threatened') and 'Threatened' (IUCN categories: 'Endangered' and 'Vulnerable').

Species	Scientific name	Feeding type	Body mass (kg)	Activity class	IUCN category
Elephant	*Loxodonta africana*	Herbivore	4000	Cathemeral	Threatened
Giraffe	*Giraffa camelopardalis tippelskirchi*	Herbivore	1340	Diurnal	Threatened
Buffalo	*Syncerus caffer*	Herbivore	550	Cathemeral	Not threatened
Zebra	*Equus quagga*	Herbivore	241.8	Cathemeral	Not threatened
Wildebeest	*Connochaetes taurinus*	Herbivore	226.5	Diurnal	Not threatened
Lion	*Panthera leo*	Carnivore	178.5	Nocturnal	Threatened
Warthog	*Phacochoerus africanus*	Herbivore	82.5	Diurnal	Not threatened
Bushpig	*Potamochoerus larvatus*	Herbivore	75	Nocturnal	Not threatened
Impala	*Aepyceros melampus*	Herbivore	56.3	Cathemeral	Not threatened
Leopard	*Panthera pardus*	Carnivore	53.3	Cathemeral	Not threatened
Hyena	*Crocuta crocuta* and *Hyena hyena*	Carnivore	50	Nocturnal	Threatened
Thomson's gazelle	*Eudorcas thomsonii*	Herbivore	23.75	Cathemeral	Not threatened
Civet	*Civettictis civetta*	Carnivore	11	Nocturnal	Not threatened
Jackal	*Lupulella mesomelas*	Carnivore	10	Cathemeral	Not threatened
Honey badger	*Mellivora capensis*	Carnivore	9.9	Nocturnal	Not threatened
Dik-dik	*Madoqua kirkii*	Herbivore	5.5	Cathemeral	Not threatened
Genet	*Genetta genetta* and *Genetta maculata*	Carnivore	2.1	Nocturnal	Not threatened

To select respondents for study participation, teams of 1–3 research assistants walked in pre-planned directions from a village centre (i.e. transects) to approach households. Selected households were located a minimum of c. 200 m apart, and households located closer than 200 m were excluded from sampling. Once a household had been chosen, the research team provided an introduction, background about the study and obtained informed oral consent from one adult member of the household (at least 18 years of age) for study participation. This included guarantees of anonymity and the right to stop participating at any time. Depending on the linguistic profile of the respondent, structured interviews were carried out either in *Maa* (for Maasai and WaArusha participants) or *kiSwahili* (Tanzania's national language).

The first section of the survey instrument established demographic information about the respondent including age, gender, ethnicity, education level and wealth (Appendix S1). Given the diversity of ethnic groups in the area, we categorized respondents into one of four categories (Maasai, WaArusha, Iraqw and Other). Since very few respondents had attended university, we disaggregated education into three levels (none, primary and secondary or more).

To determine the key livelihood strategy of the respondent, we used two main indicators: livestock holdings as represented by tropical livestock units (TLU) and land holdings in acres. To calculate TLU, we used the following conversions following standard guidelines for the region: cattle = 0.5, donkey = 0.3 and sheep/goat = 0.1 (FAO, 2011). Land and livestock holdings are potentially important for shaping the types of interactions between people and various species of wildlife that are likely to occur. Livestock keepers are particularly impacted by large carnivores, for instance, as are crop cultivators by elephants and other herbivores.

The second section of the survey instrument comprised questions about each of the 17 wildlife species included in our study. As the target variable for our analyses, we assessed if participants could identify each species correctly. We presented a colour photo plate depicting each species and asked interviewees to name the species in either *kiSwahili* or *Maa*. Based on the response, we assessed if the interviewee could correctly or fractionally identify the species (e.g. 'antelope' instead of the more specific answer 'impala'), or could not provide a correct name. We initially planned to survey at least 20 people from each of our study villages, but due to practical constraints, we were able to survey a minimum of 17 people from each village. In total, we carried out 680 structured interviews.

2.3 | Geographic variables

To take into account variation in the distributions of wildlife species (Diplock et al., 2018) as well as geographic specificity of human–wildlife encounters across our study area (Zimmermann et al., 2021), we included district of residence into our model. To

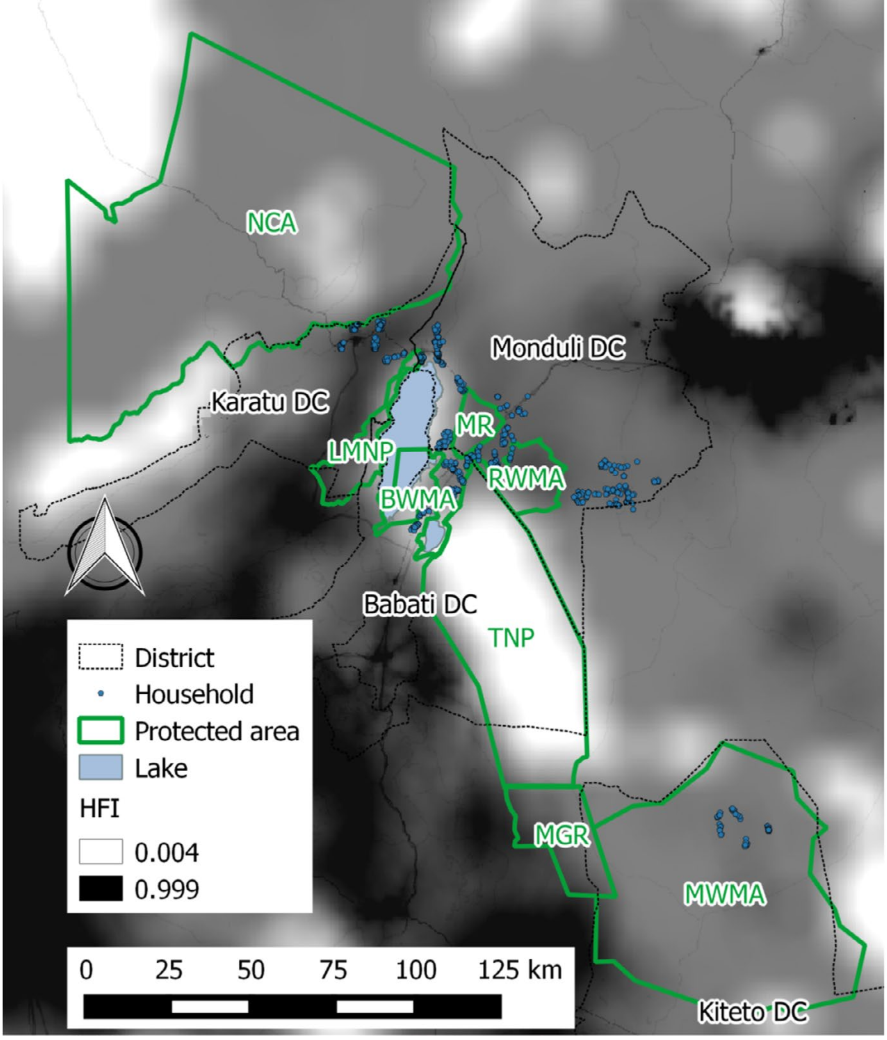

FIGURE 1 Map of the study area showing the boundaries of eight protected areas (BWMA, Burunge Wildlife Management Area; LMNP, Lake Manyara National Park; MGR, Mkungunero Game Reserve; MR, Manyara Ranch; MWMA, Makame Wildlife Management Area; NCA, Ngorongoro Conservation Area; RWMA, Randilen Wildlife Management Area; TNP, Tarangire National Park), and four districts (Karatu, Babati, Monduli and Kiteto). The map also displays locations of households selected for this study, the spatial distribution of the Human Footprint Index (HFI), and major lakes (Lake Manyara and Lake Burunge).

assess the effects of geographic variables on people's abilities to correctly identify wildlife species in a more generalizable fashion, we included Kennedy et al.'s (2019) HFI dataset and distance to the closest protected area. The HFI dataset offers a recent (2016), continuous and cumulative measure of human land use intensity, combining 13 stressors. The HFI ranges from 0, which represents no human modifications to the land, to 1, which refers to land that has been completely altered by humans. To integrate our survey data with the HFI dataset, we layered the HFI raster data with the household locations using QGIS 2.8.3 and then used the geo-processing tool to create an HFI score for each of our households (see Figure 1). Since livestock grazing and crop cultivation are not spatially restricted to the exact household location, we considered a radius of 1.94 km around the location of each household (which was recorded using a handheld GPS unit). This distance represents the median displacement of cattle in our study area (Ekwem et al., 2021) and is likely a reasonable proxy for the area in which humans interact with wildlife. To determine distance to the closest protected area in kilometres, we used the *NNjoin* function. For those households that were located within protected area boundaries, we categorized these distances as 0 km.

2.4 | Species-specific variables

We considered whether the following species-specific variables influenced identification accuracy of rural residents (Table 2): feeding category (herbivore; carnivore), body mass, activity patterns and the conservation status of the species. We also included the species ID of the animal as a random effect; this accounted for the fact that certain species were easier or more difficult to identify, irrespective of the considered traits.

2.5 | Data analysis

To analyse our data, we used R 4.2.23 (R Core Team, 2021), and fitted a generalized linear mixed model (GLMM) that accommodated the hierarchical structure of our data and accounted for both fixed and random effects. We fitted the model within the Bayesian framework and used the *brms* package (Bürkner, 2021), which allows for flexible modelling of complex data structures. We specified the model as a cumulative link mixed model, suitable for ordinal response variables, and used a logit link function to model the cumulative probabilities

of the ordinal outcomes of our target variable. We defined the target variable as an ordinal variable reflecting the identification accuracy of species by the respondents, with categories ordered as 'Incorrect', 'Fractional' and 'Correct'. This response variable was modelled as a function of several predictor variables (summarized in Table 1), while accounting for the non-independence of observations arising from the nested structure of our data.

We incorporated three levels of random effects to capture the variability across different hierarchical levels. First, we included each wildlife species as a random effect to account for the intrinsic differences in identifiability between species. Second, we included village as a random effect to accommodate the potential non-independence of responses within the same village, recognizing that respondents within the same village might share similar environmental exposures, educational backgrounds, cultural practices and local information that could influence their species identification abilities. Third, we accounted for the non-independence of multiple responses from the same respondent (i.e. each respondent answered questions about 17 species) by nesting respondent ID within village as a random effect. This structure acknowledges that respondents are not independent across villages.

Among the fixed effects, we included a variety of variables intended to capture the influence of socio-demographic factors, species-specific characteristics and geographic variables (Table 1). We selected these variables based on theoretical considerations and previous literature suggesting their relevance in influencing people's ability to accurately identify species. Prior to fitting the model, we standardized continuous variables, such as age, body mass and distance from protected areas, to have a mean of 0 and a standard deviation of 1, facilitating model convergence and interpretation of model coefficients. Additionally, we log-transformed the body mass variable before standardization to address its skewed distribution.

We estimated model parameters using four Markov Chain Monte Carlo chains, each running 2000 iterations, with the first 1000 iterations used as warm-up. This resulted in 4000 post-warm-up samples for inference. To account for the ordinal nature of our target variable, we chose the cumulative family with a logit link. We specified weakly informed priors to improve model stability while allowing flexibility in parameter estimation. For fixed effects, we used a normal distribution with a mean of 0 and a standard deviation of 2.5. For the intercept and the random effects, we used a Student's *t* distribution with 3 degrees of freedom, a mean of 0 and a scale parameter of 2.5.

To ensure the adequacy and reliability of the model fit, we conducted model diagnostics, including checks for convergence (e.g. $\hat{R}$ values close to 1) and posterior predictive checks. We compared the full model (Table S2) to a reduced model (Table S3; this model excluded all variables whose posterior estimates had 95% credible intervals [CrI] overlapping zero) using leave-one-out cross validation. The reduced model had a slightly lower predictive performance (expected log pointwise predictive density difference = −2.3; standard error of this difference = 2.6), indicating no strong justification for removing predictors. Accordingly, we retained the full model for completeness and interpretability.

To visualize the model output, we plotted the random effects for species and villages and the odds ratios of the fixed effects (OR; exponent of fixed effect estimates) and their associated 95% CrI. CrI, akin to confidence intervals in frequentist statistics, denote the range likely containing the true estimate; 95% CrIs overlapping with 1 imply that the effect is indistinguishable from no effect at this credibility level.

To evaluate the explanatory power of the fitted model, we computed conditional Bayesian R^2 scores, which consider both random effects and fixed effects, and marginal R^2 scores which consider only fixed effects, using the *performance* package (Lüdecke et al., 2021). By employing this modelling approach, we aimed to comprehensively understand the factors correlating with species identification accuracy, while appropriately accounting for the complex and nested structure of our data and the inherent variability across different levels of observation.

3 | RESULTS

Across the 25 study villages, Maasai was the most populous ethnic group (42%) followed by Iraqw (22%) and WaArusha (16%). Other ethnic groups, most of which practiced a combination of animal husbandry and crop cultivation, were grouped together as other (20%). The mean age in years was 41, and the female to male gender ratio was 0.82. Just over half of the sample (52%) had attended primary school, about a third (33%) had no formal education and a minority (15%) had been to secondary school or above. In terms of material wealth indicators, the mean farm size of respondents was 8.2 acres (0–200 range), and the mean TLU was 18.2 (0–665 range). The average distance to the nearest protected area was 5.1 km (0–28.3) and the mean HFI was 0.61 (0.32–0.85). An overview of the study sample is shown in Table S1.

3.1 | Species identification

Almost all respondents were able to correctly identify elephant (99%), zebra (98%), giraffe (97%), hyena (95%) and lion (92%) (Figure 2). The majority of respondents were also able to correctly identify buffalo (88%), leopard (88%), dik-dik (76%), jackal (74%), wildebeest (74%), impala (65%), warthog (62%) and bushpig (60%). Less than half of the respondents correctly identified Thomson's gazelle (48%), honey badger (36%), genet (31%) and civet (25%). However, a relatively large percentage of respondents fractionally identified Thomson's gazelle (31%), impala (26%), genet (20%), civet (20%), bushpig (17), warthog (14%) and honey badger (10%).

3.2 | Correlates of species identification ability

Our full model, defined as a cumulative link mixed model with a logit link function, efficiently handled the ordinal nature of our

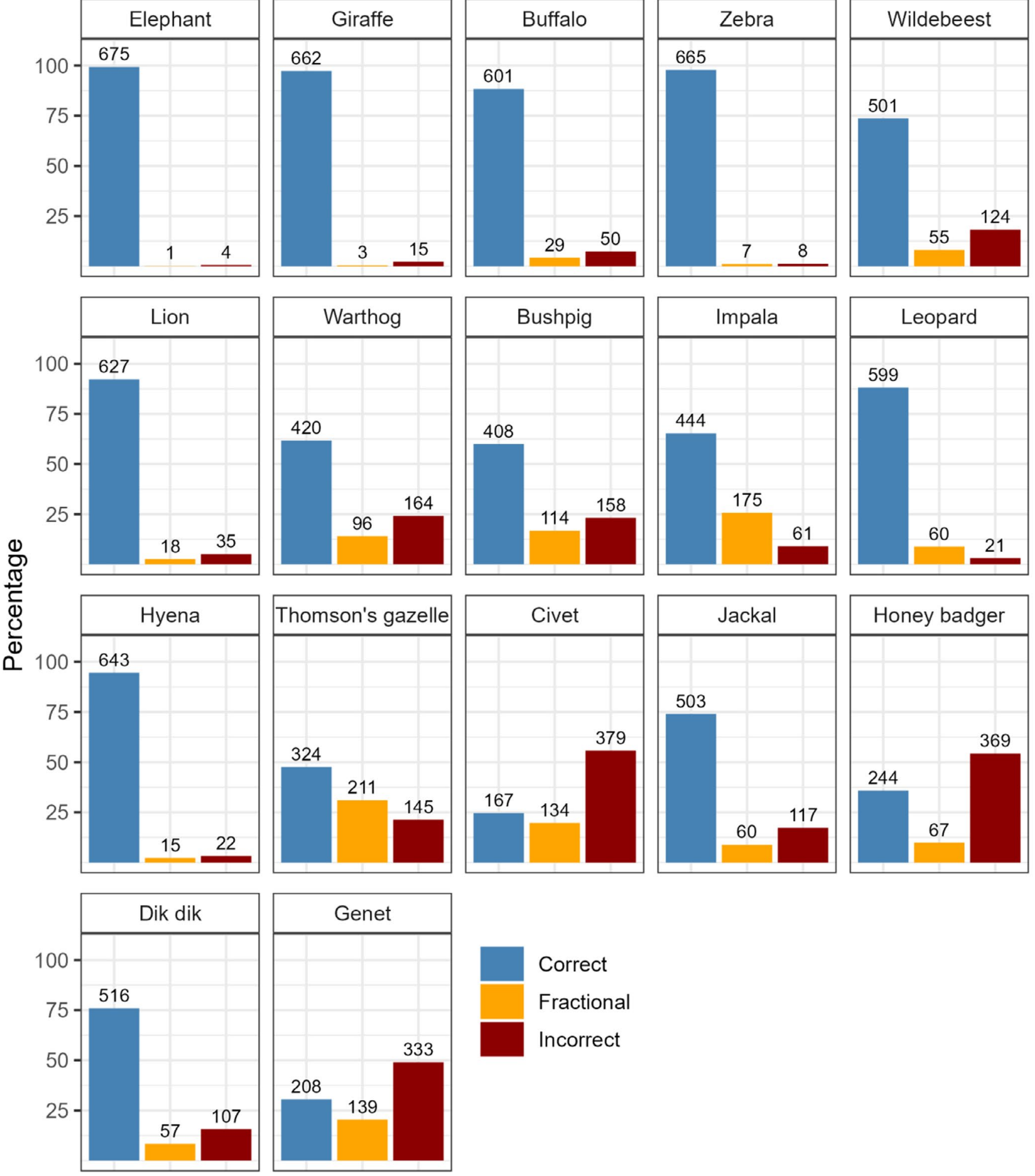

FIGURE 2 Percentage of correct, fractional and incorrect identification of 10 herbivore and seven carnivore species in northern Tanzania. Percentages are based on raw data from 680 interviews, with the number of responses displayed above each bar. Species are ordered in descending order of body mass.

target variable—categorizing species identification accuracy as 'Incorrect', 'Fractional' and 'Correct'. The model converged well as evidenced by $\hat{R}$ values reaching the ideal of 1.0 across all parameters, indicating that the model successfully reached a stationary distribution. Posterior predictive checks affirmed a good fit to the data, further validating the model's suitability for our analysis. The full model (including both fixed and random effects) explained about 55% of the variance in species identification

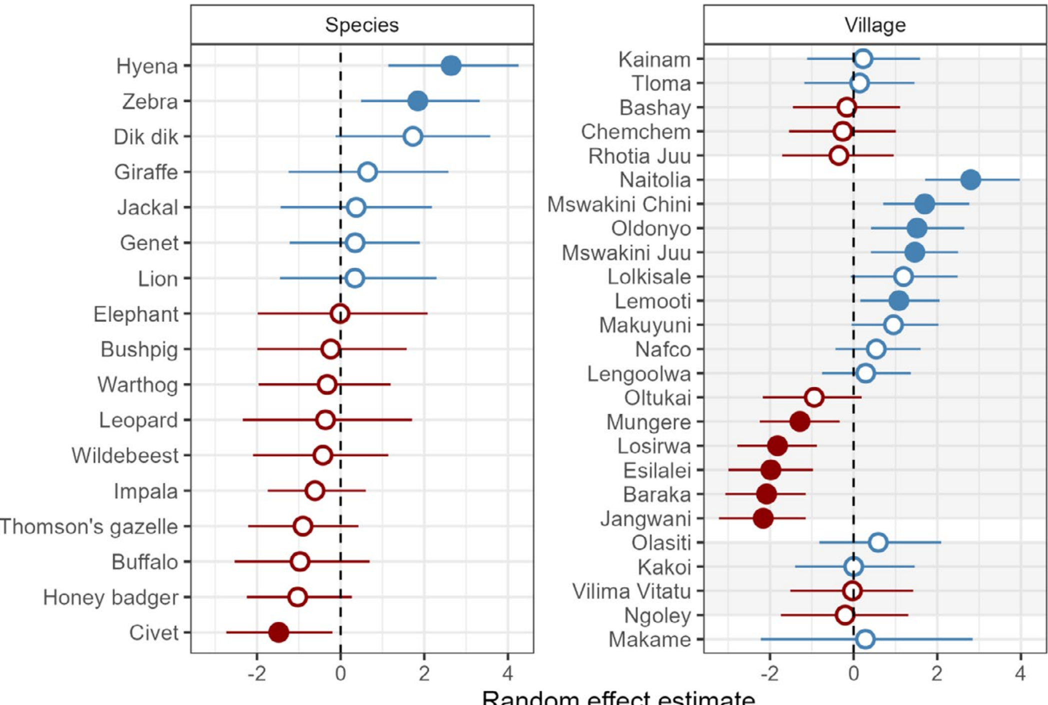

FIGURE 3 Random effects derived from a Bayesian generalized linear mixed model assessing variation in wildlife species identification accuracy among residents of rural northern Tanzania. Estimates represent random intercepts for each wildlife species (left panel), and village (right panel), reflecting how each random intercept deviates from the model's overall baseline (dashed line at zero). Random intercepts for species or villages with credible intervals overlapping zero (open circles) show little evidence of deviation from the overall average identification probability, while those with credible intervals not overlapping zero (filled circles) have strong evidence of higher (blue) or lower (red) probabilities of correct identification. Villages are grouped and ordered by district, with grey shading distinguishing the districts of Karatu (Kainam-Rhotia Juu), Monduli (Naitolia-Jangwani), Babati (Olasiti-Ngoley) and Kiteto (Makame).

accuracy (conditional $R^2=0.55$, 95% CrI [0.54, 0.56]). Fixed effects alone accounted for approximately 33% of the variance (marginal $R^2=0.33$, 95% CrI [0.20, 0.44]), indicating that random effects related to respondents, species and geographical location substantially contribute to the model's performance.

The group-level effects highlight the variability in species, villages and individual respondents nested within villages, with standard deviation (SD) estimates for the intercepts suggesting substantial differences in baseline identification accuracy across these hierarchical levels. The variation in species intercepts (SD = 1.45 [95% CrI: 0.95; 2.24]) underscores differences in the ease or difficulty of identifying certain species (Figure 3). Similarly, variability at the village level (SD = 1.45 [95% CrI: 1.03; 2.05]) suggests fine-scale spatial differences in the ability to identify wildlife species. However, the variation in baseline identification accuracy among villages does not appear to be systematically related to the district in which the villages are located. Notably, the random effects for villages in the district of Monduli were highly variable, while random effects for villages in Babati and Karatu districts had more similar effects (Figure 3). At the individual level, respondents nested within villages also showed some variation in their baseline ability to identify wildlife species (SD = 1.03 [95% CrI: 0.94; 1.14]). However, this individual-level variation is smaller than the species- and village-level variation.

Among the fixed effects, our model provides strong evidence that demographic variables (gender and education) and species-specific variables (body mass) influence identification accuracy, whereas geographic variables did not substantially influence identification accuracy (Figure 4).

Among the demographic variables, gender of the respondent strongly influenced identification accuracy, with male respondents having nearly threefold greater odds (OR = 2.94, 95% CrI: 2.39; 3.60) of more accurately identifying a given species compared to female respondents. Formal education was negatively associated with identification accuracy; primary education slightly decreased the odds of improved accuracy (OR = 0.83, 95% CrI: 0.64; 1.08), with a more pronounced decrease observed for secondary education (OR = 0.59, 95% CrI: 0.42; 0.84). Other tested demographic variables, including age (OR = 1.09, 95% CrI: 0.97; 1.21), acres under cultivation (OR = 1.11, 95% CrI: 0.98; 1.26), livestock units (OR = 1.02, 95% CrI: 0.91; 1.16), and ethnicity ($OR_{Maasai}=1.28$, 95% CrI: 0.79; 2.06; $OR_{Other}=1.21$, 95% CrI: 0.83; 1.74; $OR_{WaArusha}=0.82$, 95% CrI: 0.48; 1.37; all compared to Iraqw) showed no strong associations with identification accuracy (Figure 4).

Among the considered species-specific variables, only body mass was a strong predictor of identification accuracy. Each unit increase in log-scaled body mass increased the odds of identifying a

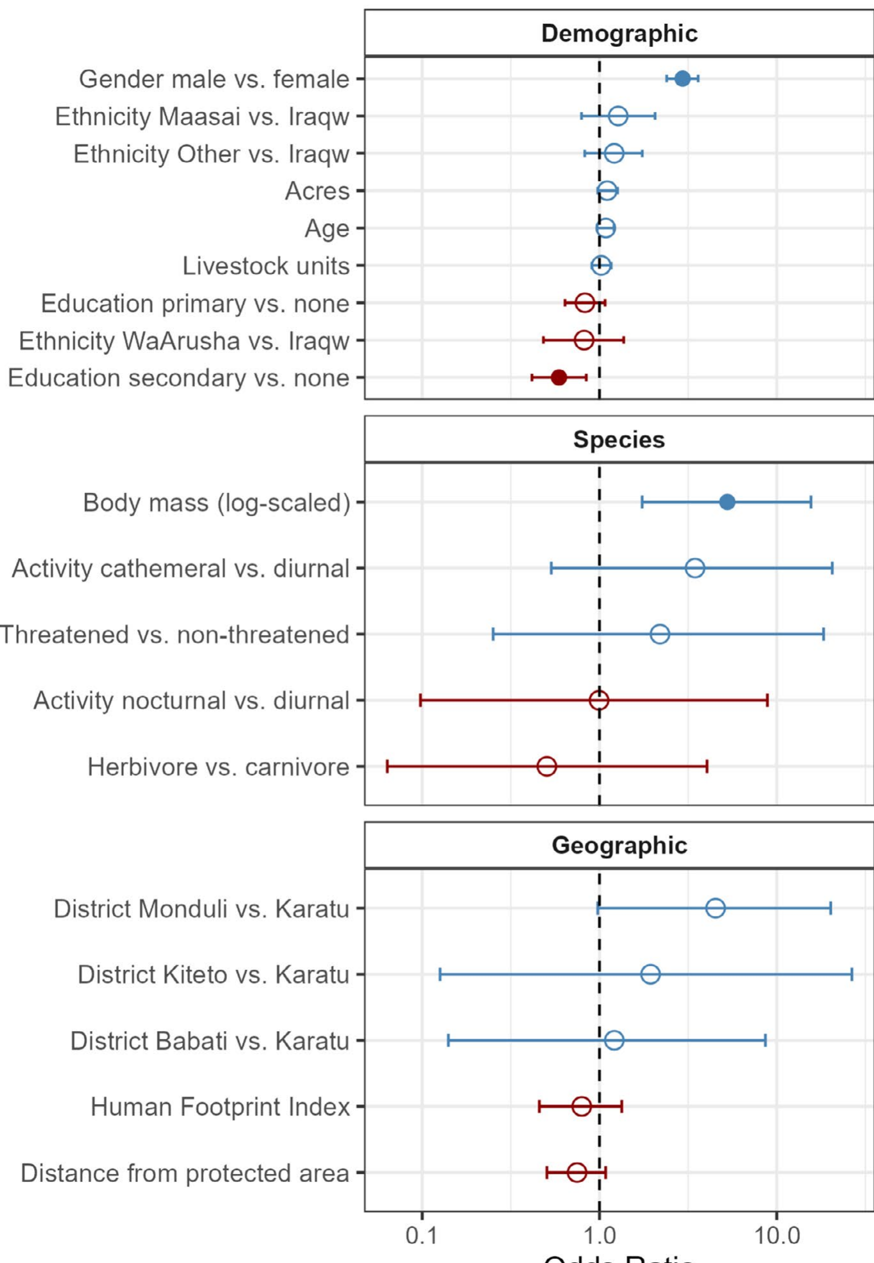

FIGURE 4 Odds ratios (OR) and 95% credible intervals derived from a Bayesian generalized linear mixed model assessing wildlife species identification accuracy in northern Tanzania, categorized by respondent demographics, species characteristics and geographical factors. OR estimates indicate the change in the odds of correct species identification for a one-unit increase in numerical variables (acres, livestock units, age, body mass [log-scaled], Human Footprint Index, distance from protected area; all scaled), or the change relative to the reference level for categorical variables (ethnicity, education, gender, feeding strategy, conservation status, activity pattern, district). The dashed line at OR = 1 indicates no effect. Estimates with credible intervals overlapping 1 (open circles) suggest little evidence of an effect, while those with credible intervals not overlapping 1 (filled circles) provide strong evidence of increasing (blue) or decreasing (red) species identification accuracy.

species more accurately by over five times (OR = 5.26, 95% CrI: 1.74; 15.60). Neither activity patterns ($OR_{Cathemeral}$ = 3.46, 95% CrI: 0.53; 20.57; $OR_{Nocturnal}$ = 0.99, 95% CrI: 0.10; 8.85; all compared to diurnal activity patterns), conservation status ($OR_{Threatened}$ = 2.19, 95% CrI: 0.25; 18.38; compared to non-threatened species) nor feeding type ($OR_{Herbivore}$ = 0.50, 95% CrI: 0.06; 4.04; compared to carnivore) strongly mediated species identification.

We found no strong support that geographical variables mediated species identification accuracy. For all variables considered, including district ($OR_{Monduli}$ = 4.52, 95% CrI: 0.98; 20.57; OR_{Kiteto} = 1.94, 95% CrI: 0.13; 26.54; OR_{Babati} = 1.21, 95% CrI: 0.14; 8.63; all compared to Karatu), HFI (OR = 0.79, 95% CrI: 0.46; 1.34), and distance to protected area (OR = 0.75, 95% CrI: 0.51; 1.08), CrI overlapped with zero, suggesting high uncertainty about their potential effects (Figure 4).

4 | DISCUSSION

Increasing recognition of the need to integrate human dimensions into wildlife research has translated into a growing number of studies on the perceptions of people that share landscapes with wildlife (Frank et al., 2019; König et al., 2020). Relying on people's reports about wildlife dynamics and HWIs assumes that they are able to accurately identify key wildlife species. If this assumption is violated, it may lead to overestimation of wildlife populations (Johansson et al., 2020), with particularly pronounced consequences for endangered species (Butchart et al., 2018). By taking a rigorous quantitative approach, our study evaluated whether rural residents across 25 villages in northern Tanzania could accurately identify key wildlife species based on a photo-naming exercise. Our results confirm that these residents can reliably

identify species commonly involved in HWIs, affirming the validity of community-reported wildlife data. However, species identification accuracy was influenced by a suite of human demographic and species-specific factors, while geographic fixed effects showed no clear pattern, though substantial village-level variation was evident. These findings highlight the importance of accounting for these biases when integrating local knowledge and context in wildlife conservation strategies (cf. Kosmala et al., 2016) and contribute to the broader discourse on the validity of local perceptions for monitoring wildlife dynamics.

4.1 | Contextualizing key results

While providing detailed information for our specific social-ecological system, our key findings partially align with studies conducted in other regions. For example, Corbett et al. (2005) concluded that wildlife (snake) reports from the general public were fairly reliable, reducing the need for independent verification by wildlife or health professionals. By contrast, other studies suggested a significant gap between laypeople and professionals (Falk et al., 2019; Hooykaas et al., 2019). In our study, people were generally able to identify wildlife species, supporting Corbett et al.'s (2005) assertion that community reports can accurately represent wildlife dynamics. Our results suggest that the perspectives of rural communities are reliable indicators for most of the mammal species considered in our study (Table 2; Figure 2).

The fact that people more accurately identified larger mammals parallels Falk et al.'s (2019) finding about the positive association between identification accuracy and distinctive species appearance, though it is difficult to generalize from their study of bee species identification, which is likely more challenging than large mammal classification. To the best of our knowledge, no pre-existing studies investigated the predictors of people's mammal identification abilities, though we see clear parallels to Callaghan et al.'s (2022) findings that larger bird species were more represented in citizen science datasets. In our case, body mass was a major predictor of species identification ability, suggesting that bigger animals are easier for people to correctly identify.

Adding further nuance to this discourse, Rögele et al. (2022) found that volunteers who received formal guidance had better species identification skills than those without direction. While guiding was not offered in our study, we assessed the influence of formal education. Interestingly, those *without* formal education identified animals more accurately. One potential explanation here is that those individuals in rural Tanzania who do not attend school may spend more time at home in the villages, participating in traditional economic and political systems such as livestock herding or farming. Secondary education in Tanzania can lead to lifestyles that are more distanced from rural ecosystem dynamics. This aligns with Bashan et al.'s (2021) finding that rural residents, having more opportunities to interact with nature, tend to have better species identification skills than their urban counterparts. It is likely in our study that traditional forms of cultural and ecological knowledge are contributing factors affecting the relationship between education and species identification ability.

Our finding that men were three times more likely to accurately identify species than women suggests that gendered conservation education and outreach programs would be of benefit in this ethnographic context (cf. Ostermann-Miyashita, Pernat, et al., 2023). The notable gender difference likely relates to traditional divisions of labour within most Tanzanian ethnic groups. For example, in Maasai society, women are usually responsible for domestic work around homesteads, while men oversee herding and crop cultivation in areas where wildlife encounters are more frequent. The result supports existing studies that showed gendered differences in species identification ability (Corbett et al., 2005; Silva et al., 2022) and associations between species exposure and species identification and knowledge (Ostermann-Miyashita et al., 2022).

The weak (and uncertain) positive relationship between age and species identification accuracy may suggest that increased life experience and more encounters with wildlife over a longer period lead to increased species literacy. Iraqw elders in Karatu district, for instance, would have been the only ones to observe some regionally extinct species near their homesteads in their lifetimes. Our finding that HFI, as a proxy of the urban–rural gradient, was not significantly associated with species identification skills does not necessarily line up with previous research results showing that rurality is generally associated with better species identification skills (Bashan et al., 2021; Panisi et al., 2022; Silva et al., 2022). Partially, this could be explained by the fact that our study area does not contain major cities (such as the densely populated areas near Arusha town; Figure 1) and we restricted sampling to rural areas. In addition, distance to nearest protected area did not markedly affect species identification skills. While unexpected, these results may indicate that exposure to (and associated basic knowledge of) these species is relatively homogeneous across the landscape or that exposure is not directly linked to the location of the homestead. Possibly, a rather uniform exposure to wildlife is facilitated by relatively abundant wildlife occurrence on village lands (Baker et al., 2022; Kiffner et al., 2016) and the fact that two main roads in our study area run along protected area boundaries, providing opportunistic wildlife observation opportunities (Kioko, Kiffner, Phillips, et al., 2015).

The key take home message from our study for decision-makers is that mammal species literacy among rural communities in northern Tanzania is high. People are generally able to accurately identify key mammal species, suggesting that studies of human perceptions could serve as reliable sources of empirical data on HWIs. Complexities related to the influence of demographic, geographic and species-specific variables suggest that tailored education and outreach activities could help improve species literacy across the study population and help ensure that the perspectives of rural residents make meaningful contributions to wildlife research and policy in the future.

4.2 | Context-specific applications of citizen science data

Citizen science data are increasingly used worldwide for monitoring wildlife and can provide reliable baseline estimates of species distribution and abundance across large spatial scales (Backstrom et al., 2024; Callaghan, Poore, Mesaglio, et al., 2021; Pernat et al., 2025; Sheard et al., 2024). When conducted over long periods, such data offer crucial insights into trends in distribution and abundance (Callaghan et al., 2023; Johnston et al., 2023; Ostermann-Miyashita, Bluhm, et al., 2023; Ringim et al., 2022; Tulloch et al., 2013). While these efforts are invaluable for informing species conservation programs, citizen science data can also serve as a bottom-up approach that substantially fosters strategies for improving human–wildlife coexistence, provided that preferences of lay people are compatible with those of scientists (Burgess et al., 2017; Callaghan et al., 2022; McKinley et al., 2017; Ostermann-Miyashita et al., 2021; Rowley et al., 2019).

If designed with low barriers for participation, wildlife data collected by herders, farmers and other rural residents could not only help monitoring wildlife populations but also map HWIs (Kauffman et al., 2016; Moussa & Mohan, 2024; Pinto et al., 2024). In turn, such data could be used to predict areas of low and high HWI risk (Miller, 2015), benefitting rural people by helping to reduce the impact of HWIs on human livelihoods. For example, this information could be used to avoid livestock grazing in high risk areas (Beattie et al., 2020), identify and prioritize areas for establishing preventative methods such as predator-proof livestock corrals (Kissui et al., 2019; Raycraft, 2024a), or establishing chilli fences to protect crops from elephants (Kiffner et al., 2021).

Given the consistently high baseline knowledge among the sampled population (especially for high conflict species such as lion, leopard, hyena and elephant), moderate guidance and training would likely suffice to ensure species identification accuracy (Kioko, Kiffner, Jenkins, et al., 2015). In addition, data quality could be evaluated based on clear criteria for assessing the evidence of species presence (Binley & Bennett, 2023; Molinari-Jobin et al., 2021). The widespread use of smartphones, capable of taking pictures and recording GPS locations, may further facilitate such efforts (Vohland et al., 2021). Engaging rural residents in this form of environmental co-monitoring and co-management (cf. Peacock et al., 2020) could be an effective method for promoting sustainable human-wildlife coexistence.

AUTHOR CONTRIBUTIONS

Justin Raycraft: Funding acquisition, project administration, conceptualization, data collection, data curation, investigation, formal analysis, writing—original draft, and writing—review and editing. Reilly Becchina: Data collection, data curation, investigation, and writing—review and editing. Danielle Bettermann: Data collection, data curation, investigation, and writing—review and editing. Stephen Koester: Data collection, data curation, investigation, and writing—review and editing. Elana Kriegel: Data collection, data curation, investigation, and writing—review and editing. Kiana Lindsay: Data collection, data curation, investigation, and writing—review and editing. Edwin Maingo Ole: Data collection, data curation, investigation, and writing—review and editing. Emily Ramirez: Data collection, data curation, investigation, and writing—review and editing. Bryan Spizuco: Data collection, data curation, investigation, and writing—review and editing. Christian Kiffner: Funding acquisition, project administration, conceptualization, software, methodology, visualization, data collection, data curation, formal analysis, investigation, writing—original draft, and writing—review and editing.

ACKNOWLEDGEMENTS

The research team thanks COSTECH and the Tanzania Wildlife Research Institute for approving this study, and the local communities for supporting the project. We sincerely thank all respondents for their time. Research by Justin Raycraft was funded by: (1) The Canadian Anthropology Society (2019–2020) through a Salisbury Award; (2) the Social Sciences and Humanities Research Council of Canada (SSHRC) via a Vanier Canada Graduate Scholarship (2019–2021), a Michael Smith Foreign Study Supplement (2019–2020), a stipend from the 'Institutional Canopy of Conservation' (ICAN) project and an Explore Grant (2024); (3) the Prentice Institute for Global Population and Economy (2023–2024); and (4) the University of Lethbridge (2023–2025) through internal grant funding. Research by Christian Kiffner was funded by the Directed Research Fund of the School for Field Studies. We acknowledge support by the Open Access Publication Fund of Humboldt-Universität zu Berlin. Open Access funding enabled and organized by Projekt DEAL.

CONFLICT OF INTEREST STATEMENT

None declared.

DATA AVAILABILITY STATEMENT

The social data presented in this paper is confidential as per ethical research protocols with human subjects.

ORCID

Justin Raycraft https://orcid.org/0000-0003-2491-3245
Reilly Becchina https://orcid.org/0009-0008-2496-1187
Elana Kriegel https://orcid.org/0009-0001-4085-2086
Christian Kiffner https://orcid.org/0000-0002-7475-9023

REFERENCES

Abra, F. D., Huijser, M. P., Pereira, C. S., & Ferraz, K. M. P. M. B. (2018). How reliable are your data? Verifying species identification of road-killed mammals recorded by road maintenance personnel in São Paulo State, Brazil. *Biological Conservation*, *225*, 42–52.

Aceves-Bueno, E., Adeleye, A. S., Feraud, M., Huang, Y., Tao, M., Yang, Y., & Anderson, S. E. (2017). The accuracy of citizen science data: A quantitative review. *Bulletin of the Ecological Society of America*, *98*(4), 278–290.

Anđić, B., Šorgo, A., Stešević, D., & Lavicza, Z. (2022). The factors which influence the continuance intention of teachers in using the interactive digital identification key for trees in elementary school science education. *EURASIA Journal of Mathematics, Science and Technology Education*, *18*(8), em2140.

Backstrom, L. J., Callaghan, C. T., Leseberg, N. P., Sanderson, C., Fuller, R. A., & Watson, J. E. M. (2024). Assessing adequacy of citizen science datasets for biodiversity monitoring. *Ecology and Evolution*, *14*(2), e10857.

Baker, M., Anderson, S. J., & Kiffner, C. (2022). Financing conservation in the 21st century: Investing in nature-based climate solutions in Makame Wildlife Management Area. In C. Kiffner, M. L. Bond, & D. E. Lee (Eds.), *Tarangire: Human-wildlife coexistence in a fragmented ecosystem* (pp. 319–337). Springer.

Barua, M., Bhagwat, S. A., & Jadhav, S. (2013). The hidden dimensions of human–wildlife conflict: Health impacts, opportunity and transaction costs. *Biological Conservation*, *157*, 309–316. https://doi.org/10.1016/j.biocon.2012.07.014

Bashan, D., Colléony, A., & Shwartz, A. (2021). Urban versus rural? The effects of residential status on species identification skills and connection to nature. *People and Nature*, *3*(2), 347–358.

Beattie, K., Olson, E. R., Kissui, B., Kirschbaum, A., & Kiffner, C. (2020). Predicting livestock depredation risk by African lions (Panthera leo) in a multi-use area of northern Tanzania. *European Journal of Wildlife Research*, *66*(1), 11. https://doi.org/10.1007/s10344-019-1348-5

Bencin, H., Kioko, J., & Kiffner, C. (2016). Local people's perceptions of wildlife species in two distinct landscapes of Northern Tanzania. *Journal for Nature Conservation*, *34*, 82–92.

Bennie, J. J., Duffy, J. P., Inger, R., & Gaston, K. J. (2014). Biogeography of time partitioning in mammals. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(38), 13727–13732. https://doi.org/10.1073/pnas.1216063110

Berkes, F., Colding, J., & Folke, C. (2000). Rediscovery of traditional ecological knowledge as adaptive management. *Ecological Applications*, *10*(5), 1251–1262.

Binley, A. D., & Bennett, J. R. (2023). The data double standard. *Methods in Ecology and Evolution*, *14*(6), 1389–1397. https://doi.org/10.1111/2041-210X.14110

Burgess, H. K., DeBey, L. B., Froehlich, H. E., Schmidt, N., Theobald, E. J., Ettinger, A. K., HilleRisLambers, J., Tewksbury, J., & Parrish, J. K. (2017). The science of citizen science: Exploring barriers to use as a primary research tool. *Biological Conservation*, *208*, 113–120. https://doi.org/10.1016/j.biocon.2016.05.014

Bürkner, P.-C. (2021). Bayesian item response modeling in R with brms and Stan. *Journal of Statistical Software*, *100*(5), 1–54. https://doi.org/10.18637/jss.v100.i05

Butchart, S. H. M., Lowe, S., Martin, R. W., Symes, A., Westrip, J. R. S., & Wheatley, H. (2018). Which bird species have gone extinct? A novel quantitative classification approach. *Biological Conservation*, *227*, 9–18.

Callaghan, C. T., Borda-de-Água, L., van Klink, R., Rozzi, R., & Pereira, H. M. (2023). Unveiling global species abundance distributions. *Nature Ecology & Evolution*, *7*(10), 1600–1609.

Callaghan, C. T., Mesaglio, T., Ascher, J. S., Brooks, T. M., Cabras, A. A., Chandler, M., Cornwell, W. K., Cristóbal Ríos-Málaver, I., Dankowicz, E., & Dhiya'ulhaq, N. U. (2022). The benefits of contributing to the citizen science platform iNaturalist as an identifier. *PLoS Biology*, *20*(11), e3001843.

Callaghan, C. T., Nakagawa, S., & Cornwell, W. K. (2021). Global abundance estimates for 9,700 bird species. *Proceedings of the National Academy of Sciences of the United States of America*, *118*(21), e2023170118.

Callaghan, C. T., Poore, A. G. B., Hofmann, M., Roberts, C. J., & Pereira, H. M. (2021). Large-bodied birds are over-represented in unstructured citizen science data. *Scientific Reports*, *11*(1), 19073. https://doi.org/10.1038/s41598-021-98584-7

Callaghan, C. T., Poore, A. G., Mesaglio, T., Moles, A. T., Nakagawa, S., Roberts, C., Rowley, J. J., Vergés, A., Wilshire, J. H., & Cornwell, W. K. (2021). Three frontiers for the future of biodiversity research using citizen science data. *Bioscience*, *71*(1), 55–63. https://doi.org/10.1093/biosci/biaa131

Charnley, S., Fischer, A. P., & Jones, E. T. (2007). Integrating traditional and local ecological knowledge into forest biodiversity conservation in the Pacific Northwest. *Forest Ecology and Management*, *246*(1), 14–28.

Clauss, M., Scriba, M., Kioko, J., Ganzhorn, J. U., & Kiffner, C. (2021). Camera-trap data do not indicate scaling of diel activity and cathemerality with body mass in an East African mammal assemblage. *Ecology and Evolution*, *11*(20), 13846–13861. https://doi.org/10.1002/ece3.8090

Corbett, S. W., Anderson, B., Nelson, B., Bush, S., Hayes, W. K., & Cardwell, M. D. (2005). Most lay people can correctly identify indigenous venomous snakes. *The American Journal of Emergency Medicine*, *23*(6), 759–762.

Crall, A. W., Newman, G. J., Stohlgren, T. J., Holfelder, K. A., Graham, J., & Waller, D. M. (2011). Assessing citizen science data quality: An invasive species case study. *Conservation Letters*, *4*(6), 433–442.

Diplock, N., Johnston, K., Mellon, A., Mitchell, L., Moore, M., Schneider, D., Taylor, A., Whitney, J., Zegar, K., Kioko, J., & Kiffner, C. (2018). Large mammal declines and the incipient loss of mammal-bird mutualisms in an African savanna ecosystem. *PLoS One*, *13*(8), e0202536.

Eisen, L., & Eisen, R. J. (2021). Benefits and drawbacks of citizen science to complement traditional data gathering approaches for medically important hard ticks (Acari: Ixodidae) in the United States. *Journal of Medical Entomology*, *58*(1), 1–9.

Ekwem, D., Morrison, T. A., Reeve, R., Enright, J., Buza, J., Shirima, G., Mwajombe, J. K., Lembo, T., & Hopcraft, J. G. C. (2021). Livestock movement informs the risk of disease spread in traditional production systems in East Africa. *Scientific Reports*, *11*(1), 1–13.

Falk, S., Foster, G., Comont, R., Conroy, J., Bostock, H., Salisbury, A., Kilbey, D., Bennett, J., & Smith, B. (2019). Evaluating the ability of citizen scientists to identify bumblebee (*Bombus*) species. *PLoS One*, *14*(6), e0218614.

FAO. (2011). Guidelines for the preparation of livestock sector reviews. http://www.fao.org/docrep/014/i2294e/i2294e00.pdf

Frank, B., Glikman, J. A., & Marchini, S. (2019). *Human–wildlife interactions: Turning conflict into coexistence*. *Conservation biology*. Cambridge University Press.

Gereta, E., Ole Meing'ataki, G. E., Mduma, S., & Wolanski, E. (2004). The role of wetlands in wildlife migration in the Tarangire ecosystem, Tanzania. *Wetlands Ecology and Management*, *12*(4), 285–299.

Gilchrist, G., Mallory, M., & Merkel, F. (2005). Can local ecological knowledge contribute to wildlife management? Case studies of migratory birds. *Ecology and Society*, *10*(1), art20.

Gorleri, F. C., & Areta, J. I. (2022). Misidentifications in citizen science bias the phenological estimates of two hard-to-identify *Elaenia* flycatchers. *Ibis*, *164*(1), 13–26.

Homewood, K. M., & Rodgers, W. A. (2004). *Maasailand ecology: Pastoralist development and wildlife conservation in Ngorongoro, Tanzania*. Cambridge University Press.

Hooykaas, M. J. D. (2022). *Species literacy: the perception and cultural portrayal of animals*. Leiden University.

Hooykaas, M. J. D., Schilthuizen, M., Aten, C., Hemelaar, E. M., Albers, C. J., & Smeets, I. (2019). Identification skills in biodiversity professionals and laypeople: A gap in species literacy. *Biological Conservation*, *238*, 108202.

Hooykaas, M. J. D., Schilthuizen, M., Albers, C. J., & Smeets, I. (2022). Species identification skills predict in-depth knowledge about species. *PLoS One*, *17*(4), e0266972.

Huxham, M., Welsh, A., Berry, A., & Templeton, S. (2006). Factors influencing primary school children's knowledge of wildlife. *Journal of Biological Education*, *41*(1), 9–12.

Joa, B., Winkel, G., & Primmer, E. (2018). The unknown known—A review of local ecological knowledge in relation to forest biodiversity conservation. *Land Use Policy*, *79*, 520–530.

Johansson, Ö., Samelius, G., Wikberg, E., Chapron, G., Mishra, C., & Low, M. (2020). Identification errors in camera-trap studies result in systematic population overestimation. *Scientific Reports*, *10*(1), 1–10.

Johnston, A., Matechou, E., & Dennis, E. B. (2023). Outstanding challenges and future directions for biodiversity monitoring using citizen science data. *Methods in Ecology and Evolution*, *14*(1), 103–116. https://doi.org/10.1111/2041-210X.13834

Katswara, T., & Mukaratirwa, S. (2021). Knowledge, attitudes and practices on African tick bite fever of rural livestock communities living in a livestock-wildlife interface area in the Eastern Cape Province of South Africa. *BMC Infectious Diseases*, *21*(1), 1–11.

Kauffman, M., Peck, D., Scurlock, B., Logan, J., Robinson, T., Cook, W., Boroff, K., & Schumaker, B. (2016). Risk assessment and management of brucellosis in the southern greater Yellowstone area (I): A citizen-science based risk model for bovine brucellosis transmission from elk to cattle. *Preventive Veterinary Medicine*, *132*, 88–97. https://doi.org/10.1016/j.prevetmed.2016.08.004

Kennedy, C. M., Oakleaf, J. R., Theobald, D. M., Baruch-Mordo, S., & Kiesecker, J. (2019). Managing the middle: A shift in conservation priorities based on the global human modification gradient. *Global Change Biology*, *25*(3), 811–826.

Kiffner, C., Albertini, M., Ede, A., Donnellan, B., Hahn, N., McGinnis, M., Nietlisbach, N., Tate, J., & Kioko, J. (2015). Performance of individual species as indicators for large mammal species richness in Northern Tanzania. *Ecological Indicators*, *53*, 70–77.

Kiffner, C., Bond, M. L., & Lee, D. E. (2022). Human-wildlife interactions in the Tarangire ecosystem. In C. Kiffner, M. L. Bond, & D. E. Lee (Eds.), *Tarangire: Human-wildlife coexistence in a fragmented ecosystem* (pp. 3–22). Springer.

Kiffner, C., Kioko, J., Baylis, J., Beckwith, C., Brunner, C., Burns, C., Chavez-Molina, V., Cotton, S., Glazik, L., Loftis, E., Moran, M., Theisinger, O., & Kissui, B. (2020). Long-term persistence of wildlife populations in a pastoral area. *Ecology and Evolution*, *10*(18), 10000–10016.

Kiffner, C., Nagar, S., Kollmar, C., & Kioko, J. (2016). Wildlife species richness and densities in wildlife corridors of Northern Tanzania. *Journal for Nature Conservation*, *31*, 29–37.

Kiffner, C., Schaal, I., Cass, L., Peirce, K., Sussman, O., Grueser, A., Wachtel, E., Adams, H., Clark, K., König, H. J., & Kioko, J. (2021). Perceptions and realities of elephant crop raiding and mitigation methods. *Conservation Science and Practice*, *3*(3), e372. https://doi.org/10.1111/csp2.372

Kioko, J., Kiffner, C., Jenkins, N., & Collinson, W. J. (2015). Wildlife roadkill patterns on a major highway in northern Tanzania. *African Zoology*, *50*(1), 17–22. https://doi.org/10.1080/15627020.2015.1021161

Kioko, J., Kiffner, C., Phillips, P., Patterson-Abrolat, C., Collinson, W., & Katers, S. (2015). Driver knowledge and attitudes on animal vehicle collisions in Northern Tanzania. *Tropical Conservation Science*, *8*(2), 352–366. https://doi.org/10.1177/194008291500800206

Kissui, B. M., Kiffner, C., König, H. J., & Montgomery, R. A. (2019). Patterns of livestock depredation and cost-effectiveness of fortified livestock enclosures in northern Tanzania. *Ecology and Evolution*, *9*(19), 11420–11433. https://doi.org/10.1002/ece3.5644

Kissui, B. M., Kisimir, E. L., Lichtenfeld, L. L., Naro, E. M., Montgomery, R. A., & Kiffner, C. (2022). Human-carnivore coexistence in the Tarangire ecosystem. In C. Kiffner, M. Bond, & D. Lee (Eds.), *Tarangire: Human-wildlife coexistence in a fragmented ecosystem* (pp. 295–317). Springer.

König, H. J., Kiffner, C., Kramer-Schadt, S., Fürst, C., Keuling, O., & Ford, A. T. (2020). Human–wildlife coexistence in a changing world. *Conservation Biology*, *34*(4), 786–794. https://doi.org/10.1111/cobi.13513

Kosmala, M., Wiggins, A., Swanson, A., & Simmons, B. (2016). Assessing data quality in citizen science. *Frontiers in Ecology and the Environment*, *14*(10), 551–560. https://doi.org/10.1002/fee.1436

Lüdecke, D., Ben-Shachar, M. S., Patil, I., Waggoner, P., & Makowski, D. (2021). Performance: An R package for assessment, comparison and testing of statistical models. *Journal of Open Source Software*, *6*, 60.

Lukyanenko, R., Parsons, J., & Wiersma, Y. F. (2016). Emerging problems of data quality in citizen science. *Conservation Biology*, *30*(3), 447–449.

McKinley, D. C., Miller-Rushing, A. J., Ballard, H. L., Bonney, R., Brown, H., Cook-Patton, S. C., Evans, D. M., French, R. A., Parrish, J. K., Phillips, T. B., Ryan, S. F., Shanley, L. A., Shirk, J. L., Stepenuck, K. F., Weltzin, J. F., Wiggins, A., Boyle, O. D., Briggs, R. D., Chapin, S. F., … Soukup, M. A. (2017). Citizen science can improve conservation science, natural resource management, and environmental protection. *Biological Conservation*, *208*, 15–28. https://doi.org/10.1016/j.biocon.2016.05.015

McQuaid, G. (2022). *Local ecological knowledge of mountain goats in the Skeena Region of British Columbia and its importance to wildlife management*. Royal Roads University.

Miller, J. R. B. (2015). Mapping attack hotspots to mitigate human–carnivore conflict: Approaches and applications of spatial predation risk modeling. *Biodiversity and Conservation*, *24*(12), 2887–2911. https://doi.org/10.1007/s10531-015-0993-6

Molinari-Jobin, A., Bereitenmoser, U., Breitenmoser, C., Černe, R., Drouet-Hoguet, N., Fuxjäger, C., Kos, I., Krofel, M., Marucco, F., Molinari, P., Nägele, O., Rauer, G., Sindičić, M., Trbojević, I., Trbojević, T., Wölfl, M., Wölfl, S., & Zimmermann, F. (2021). SCALP: Monitoring the Eurasian lynx in the Alps and beyond. *CATnews*, *14*, 50–52.

Morrison, T. A., & Bolger, D. T. (2012). Wet season range fidelity in a tropical migratory ungulate. *Journal of Animal Ecology*, *81*(3), 543–552. https://doi.org/10.1111/j.1365-2656.2011.01941.x

Moussa, L. G., & Mohan, M. (2024). Exploring citizen science applications for wildlife monitoring. *Science*, *1*, 100005.

Msoffe, F. U., Kifugo, S. C., Said, M. Y., Neselle, M. O., Van Gardingen, P., Reid, R. S., Ogutu, J. O., Herero, M., & De Leeuw, J. (2011). Drivers and impacts of land-use change in the Maasai Steppe of northern Tanzania: An ecological, social and political analysis. *Journal of Land Use Science*, *6*(4), 261–281.

Ostermann-Miyashita, E.-F., Bluhm, H., Dobiáš, K., Gandl, N., Hibler, S., Look, S., Michler, F.-U., Weltgen, L., Smaga, A., König, H. J., Kuemmerle, T., & Kiffner, C. (2023). Opportunities and challenges for monitoring a recolonizing large herbivore using citizen science. *Ecology and Evolution*, *13*(9), e10484. https://doi.org/10.1002/ece3.10484

Ostermann-Miyashita, E.-F., König, H. J., Pernat, N., Bellingrath-Kimura, S. D., Hibler, S., & Kiffner, C. (2022). Knowledge of returning wildlife species and willingness to participate in citizen science projects among wildlife park visitors in Germany. *People and Nature*, *4*(5), 1201–1215.

Ostermann-Miyashita, E.-F., Pernat, N., & König, H. J. (2021). Citizen science as a bottom-up approach to address human–wildlife conflicts: From theories and methods to practical implications. *Conservation Science and Practice*, *3*(3), e385. https://doi.org/10.1111/csp2.385

Ostermann-Miyashita, E.-F., Pernat, N., König, H. J., Hemminger, K., Gandl, N., Bellingrath-Kimura, S. D., Hibler, S., & Kiffner, C. (2023). Attitudes of wildlife park visitors towards returning wildlife species: An analysis of patterns and correlates. *Biological Conservation*, *278*, 1–13. https://doi.org/10.1016/j.biocon.2022.109878

Ostertag, S. K., Loseto, L. L., Snow, K., Lam, J., Hynes, K., & Gillman, D. V. (2018). “That's how we know they're healthy”: The inclusion of traditional ecological knowledge in beluga health monitoring in the Inuvialuit Settlement Region. *Arctic Science*, *4*(3), 292–320.

Panisi, M., Pissarra, V., Oquiongo, G., Marques Palmeirim, J., de Faustino Lima, R., & Nuno, A. (2022). An endemic-rich island through the eyes of children: Wildlife identification and conservation preferences in

São Tomé (Gulf of Guinea). *Conservation Science and Practice*, *4*(3), e12630.

Peacock, S. J., Mavrot, F., Tomaselli, M., Hanke, A., Fenton, H., Nathoo, R., Aleuy, O. A., Di Francesco, J., Fernandez Aguilar, X., & Jutha, N. (2020). Linking co-monitoring to co-management: Bringing together local, traditional, and scientific knowledge in a wildlife status assessment framework. *Arctic Science*, *6*(3), 247–266.

Pernat, N., Buchholz, S., Kriegs, J. O., Steen, J., & Hollens-Kuhr, H. (2025). Moving north under the eye of the public: The dispersal ecology of the Nosferatu spider, documented by citizen scientists. *Basic and Applied Ecology*, *84*, 40–49.

Pernat, N., Canavan, S., Golivets, M., Hillaert, J., Itescu, Y., Jarić, I., Mann, H. M. R., Pipek, P., Preda, C., & Richardson, D. M. (2024). Overcoming biodiversity blindness: Secondary data in primary citizen science observations. *Ecological Solutions and Evidence*, *5*(1), e12295.

Pierotti, R., & Wildcat, D. (2000). Traditional ecological knowledge: The third alternative (commentary). *Ecological Applications*, *10*(5), 1333–1340.

Pinto, C. M., Vargas Soto, J. S., Flatt, E., Barboza, K., & Whitworth, A. (2024). Identifying wildlife road crossing mitigation sites using a multi-data approach-a case study from southwestern Costa Rica. *Journal of Environmental Management*, *361*, 121263.

Prins, H. H. T., & Loth, P. E. (1988). Rainfall patterns as background to plant phenology in northern Tanzania. *Journal of Biogeography*, *15*, 451–463.

R Core Team. (2021). *R: A language and environment for statistical computing*. R Foundation for Statistical Computing. http://www.r-project.org/

Ratnieks, F. L. W., Schrell, F., Sheppard, R. C., Brown, E., Bristow, O. E., & Garbuzov, M. (2016). Data reliability in citizen science: Learning curve and the effects of training method, volunteer background and experience on identification accuracy of insects visiting ivy flowers. *Methods in Ecology and Evolution*, *7*(10), 1226–1235.

Raycraft, J. (2022a). Community attitudes towards Randilen Wildlife Management Area. In C. Kiffner, D. Lee, & M. Bond (Eds.), *Tarangire: Human-wildlife coexistence in a fragmented ecosystem* (pp. 109–128). Springer.

Raycraft, J. (2022b). *Wildlife conservation through the lens of pastoralism: Institutional arrangements for rangeland management in the Maasai Steppe, Tanzania* [PhD dissertation, Anthropology, McGill University].

Raycraft, J. (2023). Wildlife and human safety in the Tarangire ecosystem, Tanzania. *Trees, Forests and People*, *13*, 100418. https://doi.org/10.1016/j.tfp.2023.100418

Raycraft, J. (2024a). Human–hyena (*Crocuta crocuta*) conflict in the Tarangire ecosystem, Tanzania. *Conservation*, *4*(1), 99–114. https://www.mdpi.com/2673-7159/4/1/8

Raycraft, J. (2024b). Perceived impacts of wildlife on agropastoral food production in Northern Tanzania. *Ecology of Food and Nutrition*, *63*(3), 204–228. https://doi.org/10.1080/03670244.2024.2329978

Redpath, S. M., Young, J., Evely, A., Adams, W. M., Sutherland, W. J., Whitehouse, A., Amar, A., Lambert, R. A., Linnell, J. D. C., Watt, A., & Gutiérrez, R. J. (2013). Understanding and managing conservation conflicts. *Trends in Ecology & Evolution*, *28*(2), 100–109. https://doi.org/10.1016/j.tree.2012.08.021

Ringim, A. S., Muhammad, S. I., Bako, L. A., Abubakar, H. M., Isa, S. M., Nelly, D. J., Bajoga, A. A., Bunu, A. S., Adam, H. A., Jalo, I. M., Eveso, J. O., Mathew, E. D., Danmallam, B. A., Mador, U., Paul, J. I., Aminu, I., Lawal, A., Izang, J. I., & Abu, P. N. (2022). How citizen scientists are rapidly generating big distribution data: Lessons from the Arewa Atlas Team, Nigerian Bird Atlas Project. *Ostrich*, *93*(1), 24–33. https://doi.org/10.2989/00306525.2022.2058105

Rögele, A., Scheiter, K., & Randler, C. (2022). Can involvement induced by guidance foster scientific reasoning and knowledge of participants of a citizen science project? *International Journal of Science Education, Part B*, *12*, 94–110.

Rowley, J. J. L., Callaghan, C. T., Cutajar, T., Portway, C., Potter, K., Mahony, S., Trembath, D. F., Flemons, P., & Woods, A. (2019). FrogID: Citizen scientists provide validated biodiversity data on frogs of Australia. *Herpetological Conservation and Biology*, *14*(1), 155–170.

Sheard, J. K., Adriaens, T., Bowler, D. E., Büermann, A., Callaghan, C. T., Camprasse, E. C. M., Chowdhury, S., Engel, T., Finch, E. A., von Gönner, J., Hsing, P.-Y., Mikula, P., Rui Ying Rachel, O., Peters, B., Phartyal, S. S., Pocock, M. J. O., Wäldchen, J., & Bonn, A. (2024). Emerging technologies in citizen science and potential for insect monitoring. *Philosophical Transactions of the Royal Society, B: Biological Sciences*, *379*(1904), 20230106. https://doi.org/10.1098/rstb.2023.0106

Silva, A. B., Sales, F. A., Ferreira, L. N. d. A., Andrade, J. R., Souto, W. d. M. S., & Lopes, C. G. R. (2022). Age and fieldwork experience increase Brazilian university students' ability to identify wild mammals. *Tropical Conservation Science*, *15*, 19400829211017365.

Teel, T. L., Adams, M., Don Carlos, A. W., Bonnell, M. A., & Breck, S. W. (2022). A mixed-methods social psychology application evaluating the role of citizen science in mitigating human-wildlife conflict. *Society and Animals*, *31*(5–6), 645–668.

Truong, M.-X. A., & Van der Wal, R. (2024). Exploring the landscape of automated species identification apps: Development, promise, and user appraisal. *Bioscience*, *74*(9), 601–613. https://doi.org/10.1093/biosci/biae077

Tulloch, A. I. T., Possingham, H. P., Joseph, L. N., Szabo, J., & Martin, T. G. (2013). Realising the full potential of citizen science monitoring programs. *Biological Conservation*, *165*, 128–138. https://doi.org/10.1016/j.biocon.2013.05.025

USAID. (2013). *Tanzania wildlife management areas (WMA) evaluation: Final evaluation report*. USAID.

Valliere, J. M. (2022). Cultivating scientific literacy and a sense of place through course-based urban ecology research. *Ecology and Evolution*, *12*(6), e8985.

Vallin, J., Raycraft, J., Bettermann, D., Kioko, J., Kissui, B. M., Koester, S., Lindsay, K., Ole, E. M., Ramirez, E., Spizuco, B., Loos, J., & Kiffner, C. (2025). Variable social-ecological indicators across a Tanzanian protected area network. *Biological Conservation*, *308*, 111214. https://doi.org/10.1016/j.biocon.2025.111214

Vohland, K., Land-Zandstra, A., Ceccaroni, L., Lemmens, R., Perelló, J., Ponti, M., Samson, R., & Wagenknecht, K. (2021). *The science of citizen science*. Springer International Publishing. https://doi.org/10.1007/978-3-030-58278-4

von Gönner, J., Bowler, D. E., Gröning, J., Klauer, A.-K., Liess, M., Neuer, L., & Bonn, A. (2023). Citizen science for assessing pesticide impacts in agricultural streams. *Science of the Total Environment*, *857*, 159607.

Wilfred, P. (2010). Towards sustainable wildlife management areas in Tanzania. *Tropical Conservation Science*, *3*(1), 103–116.

Wood, B. M., Millar, R. S., Wright, N., Baumgartner, J., Holmquist, H., & Kiffner, C. (2021). Hunter-Gatherers in context: Mammal community composition in a northern Tanzania landscape used by Hadza foragers and Datoga pastoralists. *PLoS One*, *16*(5), e0251076. https://doi.org/10.1371/journal.pone.0251076

Zimmermann, A., Johnson, P., de Barros, A. E., Inskip, C., Amit, R., Cuellar Soto, E., Lopez-Gonzalez, C. A., Sillero-Zubiri, C., de Paula, R., & Marchini, S. (2021). Every case is different: Cautionary insights about generalisations in human-wildlife conflict from a range-wide study of people and jaguars. *Biological Conservation*, *260*, 109185.

SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

Table S1. Summary statistics of data associated with respondents sampled in northern Tanzania, stratified by district.

Table S2. Summary of the full Bayesian generalized linear mixed model testing the effects of demographic (age, gender, education, ethnicity, TLU [tropical livestock units], acres [land under cultivation]), geographic (PA distance [distance from nearest protected area], HFI [Human Footprint Index], district), and species-specific (body mass, feeding strategy, activity pattern, IUCN category) factors on species identification accuracy among rural residents of northern Tanzania.

Table S3. Summary of the reduced Bayesian generalized linear mixed model testing the effects of variables that showed a strong effect in the full model (Table S2) on species identification accuracy among rural residents of northern Tanzania.

Appendix S1. Questionnaire used to assess species identification accuracy among rural residents in northern Tanzania.

How to cite this article: Raycraft, J., Becchina, R., Bettermann, D., Koester, S., Kriegel, E., Lindsay, K., Maingo Ole, E., Ramirez, E., Spizuco, B., & Kiffner, C. (2025). Socio-ecological correlates of wildlife species identification across rural communities in northern Tanzania. *People and Nature*, *00*, 1–17. https://doi.org/10.1002/pan3.70085