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Review

Interweaving local, expert, and Indigenous knowledge into quantitative wildlife analyses: A systematic review

Eleanor R. Stern *, Murray M. Humphries

Department of Natural Resource Sciences, McGill University, Sainte-Anne-de-Bellevue, Quebec H9X 3V9, Canada

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A B S T R A C T

Inclusion of local, expert, or Indigenous knowledge about wildlife populations and their habitats can inform wildlife research, while also increasing knowledge holder engagement and support for wildlife conservation decisions. However, experiential wildlife knowledge accumulated over time through the personal observations of knowledge holders differs from other data based on systematic observations collected through standardized methodology such as telemetry locations or field surveys. Differences in the form and the function of these two types of wildlife information makes combining them into a single comprehensive analysis more easily encouraged than accomplished. Here, we systematically review primary literature that interweaves the experiential wildlife knowledge of diverse knowledge holders into quantitative, mixed methods analysis of terrestrial vertebrate populations and their habitats. Forty-nine studies that met our selection criteria were distributed around the globe and across terrestrial vertebrate species, but most frequently were situated in Australia, Canada, and United States and focused on large, harvested mammals including ungulates, carnivores, primates, and elephants. The most common descriptor of knowledge holders was hunters/trappers, with academic experts and community members also common. The most common analyses interweaved experiential wildlife knowledge as point observations in habitat models or as habitat covariates in habitat selection analyses. Local knowledge was also included, less frequently, in species distribution models, population models, and occupancy models. Most articles accounted for bias and uncertainty either in the knowledge elicitation stage through study design or knowledge holder selection, or in the analysis stage through regression methods. Most articles that assessed model success did so through comparison to independently collected telemetry locations or field survey data. There was wide variation in self-reported success, with the majority of authors offering neutral or positive assessments and many discussing study-specific factors contributing to model performance. Our overall assessment of these 49 studies, including 6 examples described in more detail, highlight several key challenges and solutions related to the inclusion of local, expert, and Indigenous knowledge into quantitative wildlife habitat and population analyses related to i) the incorporation of uncertainty, bias, reliability, and variation in experiential wildlife knowledge, ii) matching the scale of experiential wildlife knowledge to scale of study objectives, and iii) the appropriate use, communication, and application of experiential wildlife knowledge, including issues of consent, member checking, and knowledge co-production. We conclude with several recommendations intended to better standardize and communicate uncertainty, increase the involvement of knowledge holders in multiple stages of the research, improve validity assessment through multiple model comparisons and triangulation, and encourage more careful consideration of intellectual property protection and research ethics.

1. Introduction

The distribution, abundance, and habitat requirements of wildlife species is a knowledge priority shared by many people, communities, and organizations around the world. Biodiversity observations are used in species distribution modeling to assess impacts of global climate change (Austin and Van Niel, 2011; Bond et al., 2011) and species' overlap with localized anthropogenic impacts (Silva et al., 2017; Leu et al., 2008). Changes in population abundance over time are used to assess patterns and potential drivers of species population growth and decline (Franks et al., 2017; Busch et al., 2020) while changes in abundance across spatial gradients are used to delineate species

* Corresponding author.
E-mail address: eleanor.stern@mail.mcgill.ca (E.R. Stern).

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abundance distributions (Acevedo et al., 2014), identify barriers to dispersal (Parker et al., 2016), infer habitat quality (Johnson, 2007; Holt et al., 2013), and help to prioritize habitat protection (Morris, 2003; Sebastián-González et al., 2010; Fulbright et al., 2013).

Wildlife science has become more quantitative over the last several decades (Michener and Jones, 2012; Brennan and Marcot, 2019) at a time when the importance of experiential wildlife knowledge beyond the quantitative domain has also become better recognized (Brook and McLachlan, 2008; Thornton and Scheer, 2012). The emerging emphasis on quantification, modeling, and big data within ecological, biodiversity, and wildlife sciences (Guthery, 2008; Blanco et al., 2012; Peters et al., 2014) has been referred to as "*datafication*" and interpreted as "*a shift in priorities in the ecological sciences - from concerns about localities and interaction milieu - to a focus on the emerging concept of global biodiversity… viewed as something that can be monitored, as an object of governance*" (Devictor and Bensaude-Vincent, 2016). At the same time, there is growing recognition of the need to democratize conservation science by "*broaden[ing] the definition of science to include multiple knowledge systems (e.g., traditional and local knowledge) and expand[ing] the practice of conservation science to include the participation and objectives of all those who wish to act collectively to support the stewardship of the biosphere*" (Salomon et al., 2018). The compatibility or incompatibility of these two trajectories - towards quantification (or datafication) and/or towards interweaving (Crabtree and Klain, 2021; Hessami et al., 2021; Younging, 2018) of local knowledge and priorities - is an important and under-examined transdisciplinary challenge in wildlife and conservation science.

The experiential wildlife knowledge held by local people, communities, and Indigenous Peoples can improve understanding of wildlife populations and their habitat requirements (Shokirov and Backhaus, 2020; Su et al., 2020; Wilson et al., 2010; Low et al., 2009; Mavhura and Mushure, 2019; Popp et al., 2019). Local experiential wildlife knowledge had been shown to fill gaps in scientific understanding that may be difficult or impossible to obtain through other means (Brook and McLachlan, 2008; Popp et al., 2019), offer "multiple lines of evidence" (Service et al., 2014), identify and address seasonal, experience, and scale biases (Martinez-Levasseur et al., 2017), improve temporal transferability (Tuanmu et al., 2011), provide context for interpreting results (Abu et al., 2020), and enhance community support for and involvement in wildlife science (Salomon et al., 2018; Lute and Gore, 2014; Holsman et al., 2010) by remedying the sterile dichotomy between science and knowledge (Agrawal, 1995a; Agrawal, 1995b). Despite these many advantages, local knowledge inclusion and community partner involvement in wildlife science remains limited (Brook and McLachlan, 2008; Popp et al., 2019). Challenges to interweaving experiential wildlife knowledge in wildlife science may include skepticism in the scientific community (Gilchrist et al., 2005), the difficulty of identifying suitable knowledge holders (Davis and Wagner, 2003), the potential for local knowledge to be appropriated, marginalized, misunderstood, and misused (Nadasdy, 2021), how to assess the validity, reliability, bias and uncertainty of experiential wildlife knowledge (Gilchrist et al., 2005; Kadykalo et al., 2021), and determining how knowledge may be interwoven into science while maintaining the integrity of both knowledge approaches (Nadasdy, 2021).

Local, expert, and Indigenous knowledge can be characterized as "experience-based knowledge" (Brook and McLachlan, 2005) or "place-based knowledge" (Pascua et al., 2017; Reed et al., 2021; Zurba et al., 2019) intrinsically linked to place, sourced from personal experience, and held for the benefit of place and community (Berkes, 2017). Throughout this review, we will use the phrase *experiential wildlife knowledge* to refer to experienced-based or place-based knowledge, whether possessed by local people, Indigenous Peoples, landowners, land users, citizens, and/or experts, *knowledge holder* to refer to the people who have experiential wildlife knowledge, and *wildlife science* to refer to the acquisition and application of wildlife knowledge, whether that knowledge is experiential or more methodological, systematic, and quantitative in nature.

Although the distinctions and potential complementarity of experiential wildlife knowledge and other kinds of wildlife data, such as telemetry locations or population surveys, have been discussed frequently (Temple et al., 2020), the how-to challenge of interweaving experiential wildlife knowledge and quantitative habitat and population analyses has yet to be systematically reviewed. As wildlife and conservation science seeks to become both more quantitative and democratic this how-to challenge becomes more difficult and more important. Here we conduct a systematic review of primary literature that has included experiential wildlife knowledge into quantitative habitat and population analyses, to document the methods, successes, and limitations defining these attempts at experiential wildlife knowledge inclusion. We characterize study locations and study species, categories of knowledge holders involved and the stages of their involvement, the methods used to elicit and model their experiential wildlife knowledge, and the techniques used to accommodate potential bias and uncertainty. We also describe, in more detail, six case studies from the set of identified articles that exemplify common emerging themes and some of the successes, benefits, and limitations of experiential wildlife knowledge inclusion in quantitative wildlife science.

2. Methods

2.1. Systematic review methodology

Our search term string was defined and guided by six central themes (Table S1) that included: *Knowledge Holders*, focused on different types or groups of knowledge holders; *Inclusion*, with search string synonyms targeting articles that included or integrated knowledge; *Knowledge Area*; targeting wildlife focused articles; *Study Topic*, with search strings considered relevant to habitat use or population analyses; and *Modeling*, with search strings requiring articles to address some form of quantitative analysis. Boolean operators were used to include spelling variations, plural terms, and other string variations. A scoping phase was performed to guide a final decision on search terms. Several rounds of test-searches were done using different combinations of several search themes. Total numbers of results found were assessed, as well as quality and number of the most relevant papers from these searches. We did not include more specific wildlife names (e.g., moose, marsupial) or cultural names (e.g., Inuit, Sami) to avoid introducing regional, taxonomic, and cultural bias into our search terms. To avoid overlap with the recent review of local knowledge inclusion in aquatic and marine research (Dam Lam et al., 2019), we included a search theme to exclude the terms marine, fish, and aquatic. We focused on peer reviewed primary literature articles for this review and excluded grey literature.

We searched for English language articles published in any year in the Web of Science Core Collection. The search was conducted on September 13, 2020 and yielded an initial total of 2945 articles. Over 100 Web of Science Categories were represented by these articles, many of which categories were irrelevant to our search, which we attribute to the inclusion of the term "animal", which broadly applied to many unrelated fields such as biomedical research and laboratory science. The results were initially refined using Web of Science Categories by selecting articles which were classified within relevant categories, including wildlife, zoology, statistics, and social sciences, among others. For the 1607 articles remaining, titles and abstracts were read and an article was retained for further analysis if the following five requirements were met:

1. Primary literature, journal articles (reviews, books, and reports were excluded)
2. Studied terrestrial vertebrate wildlife at a species level (if multiple species were studied, habitat or population analyses had to be reported at a species-specific level)
3. Focused on habitat and population analyses,

4. Included local, Indigenous, or expert knowledge, and
5. Interweaved knowledge into a quantitative analysis during a pre-modeling, modeling, and/or post-modeling stage.

This screening reduced the article set from 1607 to 25 articles identified as meeting the five requirements and being suitable for the review. These 25 articles were then used as the source material for snowball collection to retrieve more articles. Articles that cited or were cited by the 25 articles retrieved from the systematic review were screened using the same sequence and protocol as described above and were retained if they satisfied the five criteria and had not already been identified. This snowball sampling added 24 new articles to the original set of 25, leading to 49 total articles identified by the systematic review and snowball sampling (Table S2) (Service et al., 2014; Abram et al., 2015; Alkhairy et al., 2020; Austin et al., 2009; Aycrigg et al., 2015; Aylward et al., 2018; Brittain et al., 2020; Brook and McLachlan, 2009; Clevenger et al., 2002; Crawford et al., 2020; Di Febbraro et al., 2018; Doswald et al., 2007; Evangelista et al., 2012; Evangelista et al., 2018; Froese et al., 2017; Gros, 1998; Irvine et al., 2009; Jordt et al., 2016; Kangas et al., 1993; Kellner et al., 2020; Kowalchuk and Kuhn, 2012; Leblond et al., 2014; Linde et al., 2012; Logan et al., 2015; Lopes et al., 2019; Lunney et al., 2009; Murray et al., 2009; O'Leary et al., 2009; Parry and Peres, 2015; Pearce et al., 2001; Pearman-Gillman et al., 2020; Pédarros et al., 2020; Phommachanh et al., 2017; Pillay et al., 2011; Polfus et al., 2014; Reza et al., 2013; Seoane et al., 2005; Skroblin et al., 2019; Smith et al., 2007; Taubmann et al., 2016; Tendeng et al., 2016; Turvey et al., 2015; van der Hoeven et al., 2004; Warren et al., 2016; Webb et al., 2019; Wilkinson and Van Duc, 2017; Yamada et al., 2003; Zeller et al., 2011; Ziembicki et al., 2013).

2.2. Summary & analysis

For each article, we identified and coded the following eight topics: i) general characteristics, ii) knowledge holder information, iii) experiential wildlife knowledge elicitation method, iv) form of experiential wildlife knowledge collected, v) quantitative analyses, vi) inclusion stage, vii) bias correction, and viii) model assessment. After reading through all articles and recording specific methods used, we determined suitable method sub-categories for each topic (i.e., within knowledge elicitation method category, subcategories included: interview, survey/questionnaire, participatory mapping, etc.). We recorded which sub-categories were employed by articles in spreadsheet tables for each topic and tabulated this predominantly categorical information for the analysis. To reduce the potential for author bias, sub-categories were identified using the same words as the authors, trying to avoid imposing our own interpretations as much as possible.

General characteristics included study area/site, year of publication, and species studied. Knowledge holder information categories reflected what the authors communicated about their location (whether they were local or non-local to the area where the wildlife were studied) and the nature of the experiential wildlife knowledge they held (Table S3). Descriptors/sub-categories for consulted knowledge holders included hunters or trappers, university-affiliated academic scientists, community members, wildlife managers, Indigenous Peoples, landowners, etc. Nine articles included knowledge holders we classified as "other", because they involved a type of knowledge holder not consulted in any other article (e.g., industry stakeholders, local enthusiasts/naturalists, tour guides, local NGO, etc.) and which did not fit any other category well. Descriptors of knowledge holders could be intersectional, with one knowledge holder representative of multiple categories if they were described this way (e.g., Indigenous AND hunter/trapper AND local). An exception to this is the descriptors "Indigenous" and "Community Member", which are mutually exclusive in our classification; knowledge holders were classified as "Indigenous" if the author described the knowledge holder to be Indigenous or Aboriginal (or belonging to a specific cultural group that self-identifies as Indigenous or Aboriginal) and as "Community Member" if the authors indicated they lived locally but made no mention of Indigenous-identity. Three articles did not provide enough information to discern which type of knowledge holders were involved and were therefore classified as "Unknown".

Wildlife elicitation method described how knowledge was collected from knowledge holders, and we divided categories based on method (e.g., interview, participatory mapping, etc.) and location (e.g., in-person, online, mail, etc.) (Table S4). To assess at which stages of a study knowledge holders were involved, we defined five separate stages: *Consultation/Study Design*, in which knowledge holders were involved in planning study methodology including appropriate elicitation methods, what knowledge should be collected, how to include it, etc.; *Pre-Modeling/Analytical Approach*, in which knowledge holders were involved in developing model parameters such as study area, scale, or time frame, selecting model covariates or GIS layers to use, or directly developing statistical models; *Modeling/Data*, in which experiential wildlife knowledge in the form of observations, or quantitative information was directly included as model inputs; *Post-Modeling/Validation*, in which knowledge holders were involved in model validation, refinement, and re-parameterization; and *Follow-Up/Member Checking*, in which knowledge holders were engaged after analyses were completed to assess whether results appropriately interpreted and reflected their knowledge. We then determined whether the article described knowledge holder involvement in any or all of these stages (our results here indicate only what was discussed in the published article; it is possible that articles did not report all stages of inclusion). Different stages of knowledge holder inclusion were not necessarily conducted with the same knowledge holder, as different sets of individuals or types of knowledge holders were sometimes used in different phases of the study. To summarize bias correction and assessment, where methodologies are very context-specific and not easy to categorize without losing important nuance, we report the methodologies used in articles and discuss where trends or similarities occur.

Meta-analyses were not conducted for several reasons: i) not all papers conducted a quantitative assessment of their models; ii) assessing model success was not the focus of this review, and iii) the practice of quantitatively assessing experiential wildlife knowledge models, particularly through comparison to models based on independent data, has been criticized (Brook and McLachlan, 2005). As such, we focused on a qualitative synthesis of articles, summary tables and figures, and exploration of case studies. Six case study articles, which we describe in more detail, were chosen from the complete set of 49 articles based on the relevance and importance of each to the focus of our review as well as their collective diversity in helping to communicate the variety of approaches, opportunities, and challenges involved.

3. Results

3.1. Study location, date, and taxonomic coverage

The articles were globally distributed, including every continent except Antarctica (Fig. 1A). Countries with the most studies included Australia (10), Canada (8), and the United States (8). The articles spanned a publication timeline of nearly 30 years with the earliest article published in 1993 and more articles appearing in the last 10 years than in the 20 years prior to that (Fig. 1B). The majority of the articles (32 of 49) were single-species focused, with an additional 11 articles focused on 2–10 species, 3 articles focused on 11–20 species, and one article that focused on 50 species. The highest number of species studied was described by Aycrigg et al. (2015) as "over 6000 taxa". This article, along with another that did not specify species to the genus level, are not included in taxonomic coverage summaries. A total of 128 genera were considered by the 47 studies that specified to genus level, including 2 amphibian genera, 4 reptilian genera, 16 avian genera, and 106 mammalian genera. Commonly studied mammal groups included even-toed ungulates (e.g., bovids, suids, and cervids), carnivores (e.g., canids,

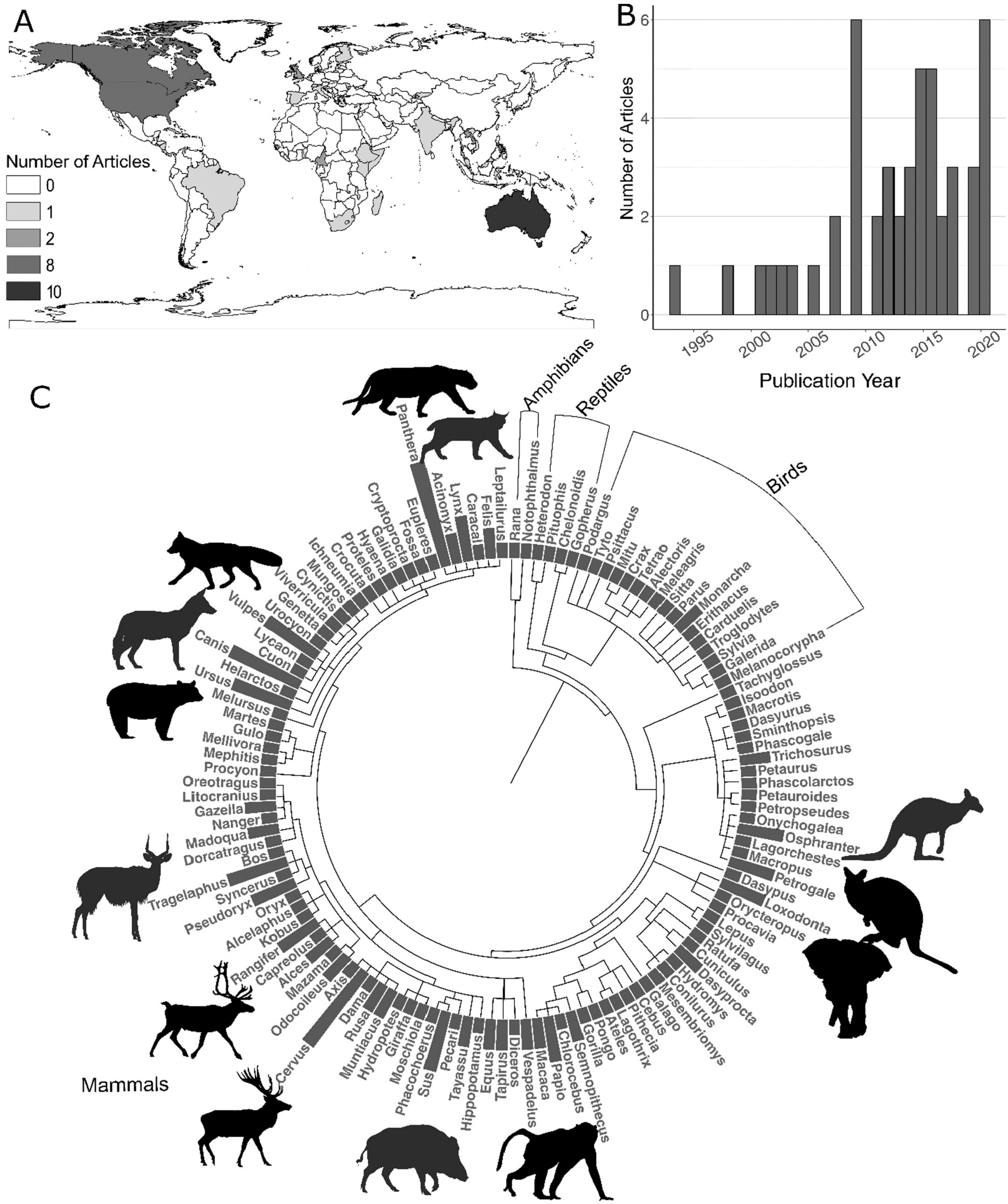

Fig. 1. Global distribution (A, articles per country), year-of-publication (B, articles per year), and taxonomic coverage (C, articles per genus arranged in a circle phylogeny based on National Center for Biotechnology Information (NCBI) Taxonomy (Schoch et al., 2020)) of journal articles describing inclusion of local experiential wildlife knowledge in quantitative analysis identified through a systematic review (date unlimited – 2020).

felids), primates, and elephants, with the most frequently studied mammalian genera including leopards or panthers (*Panthera*, 7 articles), red deer or elk (*Cervus*, 5 articles), and wolves or relatives (*Canis,* 5 articles) (Fig. 1C).

3.2. Knowledge holders

The number of knowledge holders that experiential wildlife knowledge was elicited from ranged from 1 to 16,526 with a median of 32. Most articles exclusively involved local knowledge holders (40 of 49 articles), but five articles involved a combination of local and non-local knowledge holders, and the remaining four articles relied solely on non-local experts (Fig. 2B). The most frequent descriptors for consulted knowledge holders were hunters or trappers (17 articles), university-affiliated academics (15 articles), and community members (14 articles; Fig. 2C). Less frequently included knowledge holder types included wildlife managers (9 articles), Indigenous People (6 articles) and landowners (5 articles).

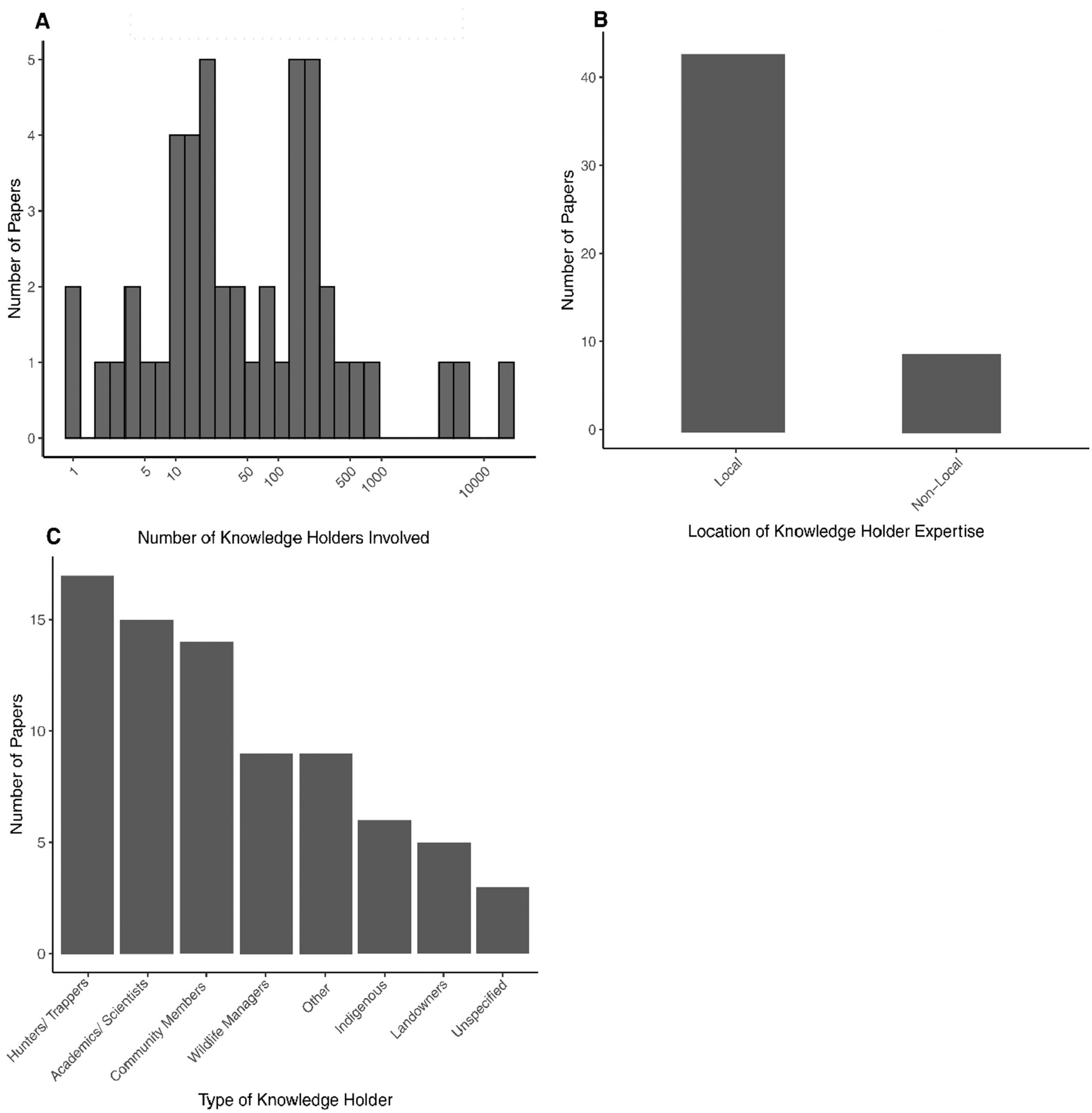

Fig. 2. Number of articles in systematic review including A) different numbers of knowledge holders, B) local and non-local knowledge holders, and C) different knowledge holder types.

3.3. Knowledge elicitation method

The most common methods of knowledge elicitation were interviews (26 articles) followed by surveys or questionnaires (18 articles; Fig. 3). Less frequent elicitation methods included participatory mapping sessions, workshops, and collecting pre-existing datasets, typically in the form of hunting records or observation records (Fig. 3). Most experiential wildlife knowledge was elicited in-person, usually in interviews, participatory mapping sessions, or in-person questionnaires or surveys, but some studies elicited knowledge online or through mail (Fig. 3.). Mail delivery was used with both large groups, small groups, or individual knowledge holders. For example, Lunney et al. (2009) sent over 100,000 participatory mapping forms across koala (*Phascolarctos cinereus*) range in Australia. Other articles sent mails surveys to several thousand landowners (e.g., Jordt et al., 2016), smaller numbers of registered hunters or trappers (e.g., Linde et al., 2012), and some others sent mail surveys to several specific individual experts (e.g., Gros, 1998). Two articles elicited experiential wildlife knowledge online using a web-based survey interface (Aylward et al., 2018; Pearman-Gillman et al., 2020).

3.4. Stage of knowledge holder involvement

Most articles involved knowledge holders in only one stage (29 of 39 articles), less than half in two stages (16 articles), relatively few in three stages (5 articles) and none in more than three stages (Fig. 4). Knowledge holders were most frequently included in the modeling/data stage (44 articles), followed by pre-modeling/analytical approach (15 articles), consultation/study-design (6 articles), post-modeling/validation (4 articles), and follow-up/member-checking (3 articles). If knowledge holders were involved in two stages, it was most often in the pre-modeling/analytical-approach and modeling/data stage (8 articles) and only one article included knowledge holders in both the consultation/study design and follow-up/member-checking stage.

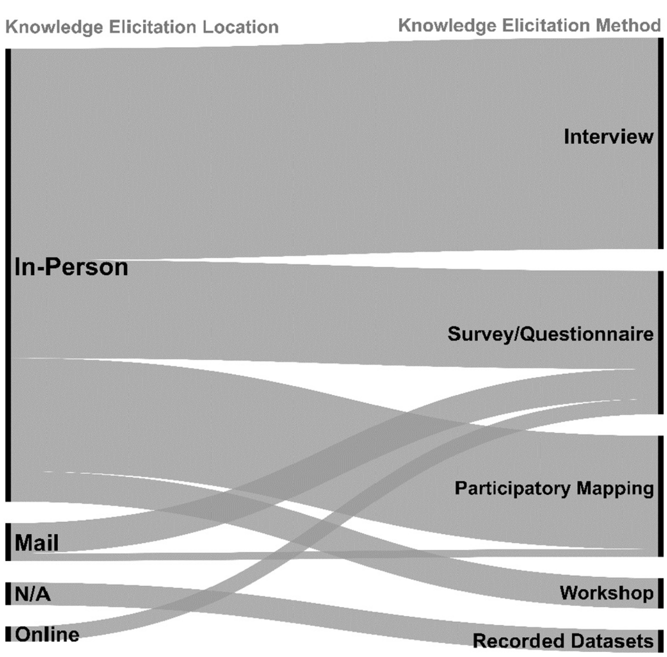

Fig. 3. Knowledge elicitation approaches presented as an association between location (left) and method (right). Width of black side bars indicate total frequency of locations and methods across all studies. Width of connecting bands indicates the frequency of each location and method combination. Four papers classified as "N/A" for location were due to the knowledge being collected through existing datasets, typically hunter records.

3.5. Experiential wildlife knowledge into quantitative models

Multiple combinations of knowledge form, statistical models, and general model topics occurred across the review articles (Table S5, Fig. 5). The most frequent combination was habitat models produced by "other regression" (neither Bayesian nor mixed model regressions) statistical methods using knowledge in the form of point observations. The next most frequent combination was habitat models produced by Generalized Linear Models (GLMs) or Generalized Linear Mixed Models (GLMMs) using knowledge in the form of either model covariate ranking, values, or coefficients, or in the form of habitat relationship networks.

Habitat models, focused on predicting or modeling habitat use or quality by species, were most prevalent across articles. Many statistical methods were used to perform these models, with the most frequent being GLMs or GLMMs, Bayesian Models, other regressions, and weighted combinations. Articles focused on habitat models typically collected knowledge in the form of i) observations or occurrence, ii) extent of distribution or presence/absence in certain areas, iii) selecting or informing key habitat covariates in the models, or iv) estimating habitat covariate ranking, importance, weighting, or coefficients. Other forms of knowledge contributing to habitat models included annotated maps, information on spatial and temporal trends, building habitat relationship networks, habitat covariate use estimates, and parameterizing or developing models. Species distribution models were similar to habitat models and employed similar statistical methods and knowledge forms, with the addition of Maximum Entropy (MaxEnt) methods being frequently used. Articles that focused on population modeling typically employed regression methods and collected knowledge in the form of observations or occurrence, information on population trends over time, and estimates of abundance or frequency. Most spatial or mapping methods were performed in ArcGIS (ESRI, 2011) or Maxent (Steven et al., 2017). Statistical analyses were generally performed in R (Core Team, 2020), STATA (StataCorp, 2021), SAS software (SAS Institute Inc, 2013), or PRESENCE (MacKenzie and USGS, 2021). Additional studies developed models with more specialized software packages including InVEST (Di Febbraro et al., 2018; Sharp et al., 2018), FunConn (Evangelista et al., 2012; Theobald, 2006), SwiColBM (Jordt et al., 2016; Lange et al., 2012), and PageRank simulations (Wilkinson and Van Duc, 2017).

3.6. Bias correction

Articles describing methods used to compensate for potential bias or error in knowledge-based information applied these methods during knowledge holder selection, knowledge elicitation, or in the modeling stage. Methods to reduce bias that focused on knowledge holder selection included identifying reliable experts using focus groups (Brittain et al., 2020), selecting respondents based on ability to identify species and/or species presence (Abram et al., 2015; Gros, 1998; Parry and Peres, 2015), selecting respondents based on hunting experience with the focal species (Linde et al., 2012), deliberately selecting respondents who did not specifically see the species (Turvey et al., 2015), or other methods of establishing reliability or "vetting" respondents

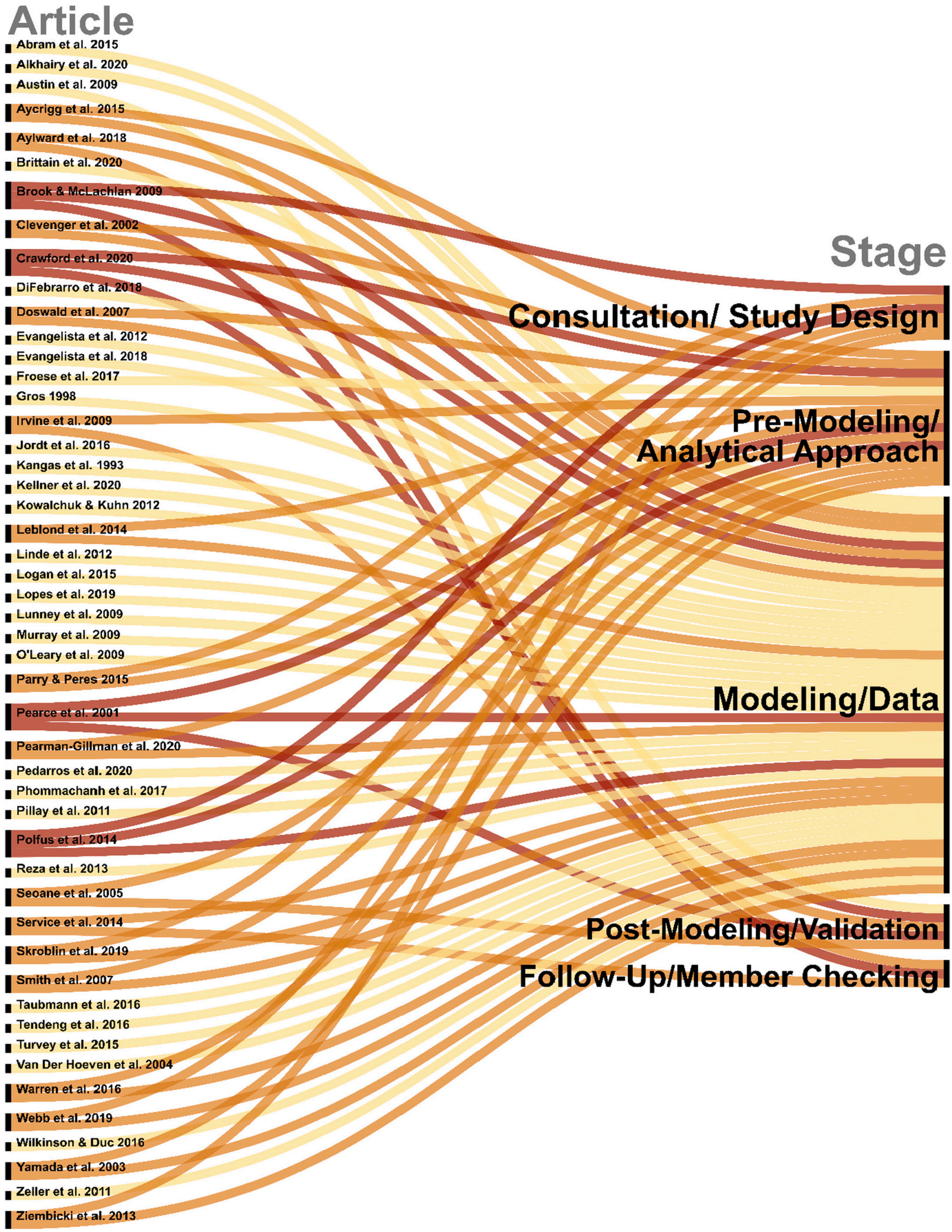

Fig. 4. Alluvial chart depicting knowledge holder inclusion across five study stages. Colors represent the number of stages knowledge holders were included (yellow = 1 stage, orange = 2 stages, red = 3 stages). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

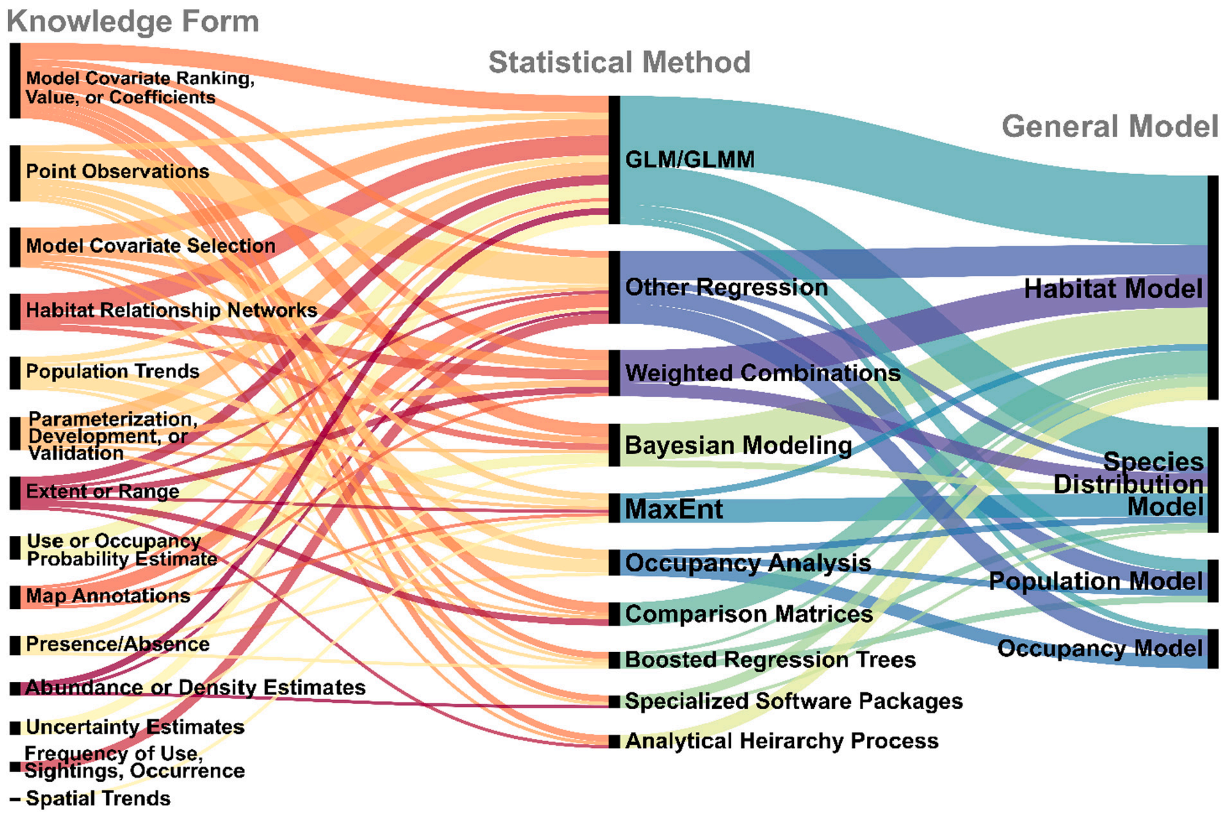

Fig. 5. Alluvial chart depicting relationships between knowledge form (left), statistical methods (middle), and general models (right). Width of the bars indicates frequency of occurrence across all articles, and width of bands between bars represents occurrence frequency for combinations of knowledge form and statistical method or statistical method and general model. Colors highlight connections but do not indicate magnitude or other distinctions.

(Phommachanh et al., 2017; Zeller et al., 2011; Ziembicki et al., 2013). Methods that focused on reducing bias through interview questions included interviewing knowledge holders individually to prevent audience-effect bias (Brittain et al., 2020), phrasing questions neutrally (Brittain et al., 2020), concealing the focal species during interviews (Brittain et al., 2020; Turvey et al., 2015), using the "interview funnel approach" (Brittain et al., 2020), and openly discussing the research objectives and species prior to interviews (Parry and Peres, 2015). Methods to reduce bias focused on the knowledge collection stage included validating reliability by asking respondents to repeat their reports of species detections at the end of the interview and removing unsure or inconsistent responses (Brittain et al., 2020), providing model feedback to experts during knowledge elicitation sessions to reduce cognitive bias (O'Leary et al., 2009), screening the dataset for reliability by cross validating interviewee responses and removing knowledge holders who gave incompatible answers as well as removing brief responses (Abram et al., 2015), and cross examining key knowledge holders (Pillay et al., 2011). After knowledge collection, statistical methods used to reduce bias in data included: using triangulation techniques to verify quality and respondent reliability (Abram et al., 2015), evaluating consistency and reliability matrices based on consistency ratio (Doswald et al., 2007; Kangas et al., 1993), assigning knowledge holders a reliability score and using that to filter or remove potentially biased data (Gros, 1998; Logan et al., 2015). Modeling methods of bias correction included using mixed-model approaches (Pearman-Gillman et al., 2020), highly weighting responses or sites where confidence was strong (Pearman-Gillman et al., 2020), entering respondents into models as a random effect or intercept (Aylward et al., 2018; Lunney et al., 2009), incorporating reliability scores into models (Gros, 1998; Logan et al., 2015), incorporating road, distance, or site-accessibility as a covariate to account for accessibility bias (Pédarros et al., 2020; Skroblin et al., 2019), or standardizing observations (Service et al., 2014).

3.7. Uncertainty

Experiential wildlife knowledge uncertainty was most frequently interweaved using Bayesian modeling (Alkhairy et al., 2020; Froese et al., 2017; O'Leary et al., 2009) or Bayesian Belief Networks (Smith et al., 2007). Some articles directly elicited uncertainty estimates from knowledge holders by having experts define their own overall uncertainty in their judgements (Froese et al., 2017; Pearman-Gillman et al., 2020) or estimate uncertainty in the form of standard deviation (Aylward et al., 2018). In other articles, the authors estimated knowledge holder uncertainty by estimating "reliability codes" for data representing confidence in the information correctness (Ziembicki et al., 2013) or by estimating expert impact and confidence for each variable and converting them to Bayesian priors (O'Leary et al., 2009). Other methods included averaging model parameters to incorporate model selection uncertainty (Logan et al., 2015), including variation or bias in knowledge holders responses by incorporating individual knowledge holder as random effects in mixed-effects models (Aylward et al., 2018; Lunney et al., 2009; Pearman-Gillman et al., 2020).

3.8. Model assessment

Around half of the articles (24 of 49) described attempts to validate or compare experiential wildlife knowledge to other sources of information. Most commonly, model outputs or predictions were compared to either an independent dataset or the dataset used in the authors model that was derived from telemetry locations or other population surveys (11 articles). Specific statistical methods included area under curve

(AUC) (3 articles), Kappa Index (3 articles), Boyce Index (2 articles), sensitivity analysis (2 articles), and spearman rank coefficients (2 articles). Numerous other methods were represented in individual articles, including contrast validation index, correct classification rate, deviance information criterion (DIC), field validation, goodness of fit, jack-knifing techniques, Mann-Whitney statistics, marginal and conditional R (Bond et al., 2011), specificity analysis, true skill statistic, and z-test.

Authors generally described the outcomes of these assessments in terms of consistency with independent data or similarity to models developed from other data such as GPS, VSH, or field-survey data. While this metric of success is flawed (see introduction and discussion), here we report the authors self-described assessment outcomes. Of the articles who assessed performance, many reported that models interweaving wildlife knowledge moderately to very accurately matched independent or original data, or performed satisfactorily to very well (Abram et al., 2015; Di Febbraro et al., 2018; Doswald et al., 2007; Froese et al., 2017; Jordt et al., 2016; Leblond et al., 2014; Pearman-Gillman et al., 2020; Polfus et al., 2014; Wilkinson and Van Duc, 2017). Some authors reported that models interweaving wildlife knowledge performed differently under different circumstances (Evangelista et al., 2018; Irvine et al., 2009; Murray et al., 2009; Pearce et al., 2001; Smith et al., 2007), with some reporting differences in the predictive accuracy of high and low suitability sites (Smith et al., 2007), or between two different kinds of models (e.g., Maxent and Boosted Regression Tree (Evangelista et al., 2018)), or based on the scale of comparison (Irvine et al., 2009). Some authors found that experiential wildlife knowledge lowered accuracy of models (Evangelista et al., 2012) or reported that the accuracy of pure experiential wildlife knowledge models was less than independent data alone (Pearce et al., 2001) and that increasing experiential wildlife knowledge input resulted in decreasing predictive ability (Seoane et al., 2005). Articles that developed and compared both experiential wildlife knowledge and independent data models report mixed results, with some reporting significant agreement between datasets (Brook and McLachlan, 2009; Clevenger et al., 2002; Pédarros et al., 2020; Tendeng et al., 2016) and others finding few similarities between wildlife knowledge and independent data based models (Kowalchuk and Kuhn, 2012).

4. Case studies

4.1. *Murray et al. (2009): an example of distribution analysis and bayesian logistic regression using expert knowledge*

Murray et al. (2009) aimed to assess uncertainties in expert opinion using Bayesian logistic regression, using three Bayesian statistical models: 1) expert-only model, 2) field-data only model, and 3) combined expert and field data model. Nine experts with backgrounds in conservation management and knowledge of rock-wallaby (*Petrogale* spp.) ecology and habitat were included, some of which was local experience. A GIS software tool was used to facilitate experiential wildlife knowledge inclusion into modeling. Regression coefficients were obtained by asking questions to assess the probability of presence at sites with known habitat characteristics. Coefficients were then used as prior distributions suitable for Bayesian analysis. Bayesian logistic regression, performed in WINBUGS 1.4 (Lunn et al., n.d.), was used to fit models via Markov chain Monte Carlo simulations. The authors found differences in posteriors formed from expert- informed informative priors and non-expert-informed non-informative priors, indicating that experts were contributing information that extended beyond the field-collected data. The deviance information criteria (DIC) showed that a combination of field data and expert-informed priors provided improved goodness-of-fit relative to non-expert informed models. Predictive performance checks indicated that models built on expert knowledge and field data performed consistently well, however all three models performed well overall. They concluded that expert knowledge, in the form of informative priors in Bayesian modeling, enhanced estimates.

4.2. *Polfus et al. (2014): an example of HSIs, RSFs, and indigenous experiential wildlife knowledge*

Polfus et al. (2014) developed a Traditional Ecological Knowledge (TEK) model and a “western science” model to study caribou habitat. These models were then compared using k-fold cross validation and spatial Kappa statistics to assess differences between models. TEK was collected through in-person, individual, semi-directed (i.e. interviewer had loosely structured questions and allowed topic to follow natural course) interviews with 8 experts, including hunters, gatherers, and community elders. TEK collected information including seasonal use and food resources, drawings of important areas, animal locations, and habitat requirements such as land cover types, habitat associations, seasonal foraging, and other seasonal resources. Habitat descriptions in TEK were linked to spatial resource covariates in the habitat model. From these variables, rule-based Habitat Suitability Index (HSI) models were developed for summer and winter. Models were built by applying these values to combinations for ecological conditions in ArcGIS by overlaying raster layers into one final map layer. The authors then used independent VHF collar data to assess the predictions made by the knowledge-based HSI model and the collar data-based Resource Selection Function (RSF) model. Spearman's rank correlation was used to assess the strength of association between knowledge and data. Further visual examination was used to assess discrepancies between the RSF and HSI models, and a weighted Kappa statistic was further used to statistically compare the two. The authors found high correlation between the RSF model and caribou locations, as well as between the HSI model and caribou locations. Visual comparison found that most discrepancies arose from the RSF predicting more high value habitat than the HSI. The Kappa statistic indicated generally strong spatial agreement between the knowledge based HSI and the data-based RSF.

4.3. *Abram et al. (2015): an example of population trend analysis, boosted regression trees, and community expert knowledge*

Abram et al. (2015) aimed to reconstruct recent population trends of orangutans (*Pongo pygmaeus*) in Indonesia. Experiential wildlife knowledge was collected in questionnaire-based interviews with villagers, and included the number of individuals seen in the previous year and their locations as well as perceptions of population change over times. Reportings of the number and location of recent observations produced georeferenced presence-only occurrence data derived from sightings. Reporting of perceived population change generated population trend responses that were categorical in nature, with respondents asked to indicate whether the contemporary population compared to 10 years ago was ‘more than now’ (1), ‘same as now’ (2), ‘fewer than now’ (3), ‘locally extinct’ (4), or ‘never seen orangutans here’ (5), with the associated numbers representing the values the answers were coded as in the dataset. Questions were converted to continuous response variables and condensed to village averages. Predictive modeling was performed on the data, with response variables including frequency of sightings and perceptions of orangutan populations. ArcGIS was used to average survey responses and allocate 39 spatial predictor variables to each village coordinate. R-based Boosted Regression Trees (BRT) were used to develop predictive models from the summarized ArcGIS output. Model outputs were mapped using ArcGIS, and the correlation between observed and predicted values was used to assess predictive performance of the models. Abram found that the BRT model for orangutan sightings performed “well”, and the BRT model on perceived orangutan population change performed “excellently”.

4.4. *Smith et al. (2007): an example of Bayesian Belief Networks to produce habitat suitability models using scientist expert knowledge*

Smith et al. (2007) aimed to demonstrate how Bayesian Belief Networks (BBNs) developed by a small group of experts could be used to study habitat suitability of Julia Creek dunnart (*Sminthopsis douglasi*) in Queensland, Australia at a region scale. The habitat suitability model was developed in two stages: i) conceptual model development and ii) creation of predictive models from conceptual models. Conceptual model development was conducted to build an influence diagram that depicted important environmental variables for habitat. The process was broken into four main steps: 1) literature review, based on published literature, theses, and research reports, 2) a meeting with a region and species expert used to build a draft influence diagram from the review findings and expert information (with the influence diagram being composed of habitat variables that influence suitability, GIS variables that could represent those key habitat variables, and environmental variables that influence key habitat variables), 3) surveys sent to 10 ecologists with specific expertise in the region and species so that their opinions on the draft could be collected and the diagram revised based on the feedback, and 4) the revised draft was then sent to two other experts for final review, and was continually revised until both of these experts were satisfied with the influence diagram. Predictive model development was done in four steps: 1) converting the revised influence diagram from the first stage into a BBN using Netica™ software (Norsys Software Corporation, 1998), 2) scenarios were constructed from the different node combinations, with associated predictions and probabilities, 3) sensitivity analysis was performed to assess relative influence between variables using Netica's entropy reduction to measure sensitivity, using expert consultation, and 4) the BBN was developed into a habitat suitability model using ArcGIS. The authors assessed accuracy of the BBN derived habitat suitability model through comparison to field survey data using the error matrix method and the Kappa statistic. They found high accuracy of model predictions with overall accuracy being 89%, however this varied based on site quality, with low quality sites predicted better than high quality sites.

4.5. *Pearce et al. (2001): an example of multi-stage inclusion of experts in distribution analysis using logistic regression*

Pearce et al. (2001) investigated several approaches of incorporating expert opinion into species distribution models at different stages for 16 species including reptiles, birds, marsupials, and bats in Australia. A panel of three experts were included in the pre-modeling, model-fitting, and post-modeling stages. Expert knowledge was included by: i) modifying or refining existing statistical models by specifying additional rules in order to refine predictions to better reflect their knowledge, ii) deriving vegetation index maps and developing a new GIS layer for each species and defining the habitat-value indices, iii) selecting predictor variables for each species, specifying the form of the relationship between species and variable, and refitting the GAM model to reflect their choice, and iv) creating models based purely on expert opinion by developing models by combining available GIS layers and creating new vegetation variables as needed. The authors assessed predictive accuracy as varying significantly between models. Multiple Pairwise Comparisons suggested that models which were developed using only expert-defined rules performed significantly worse than models which included less expert-opinion. They determined that models derived from knowledge-based vegetation indices were not significantly more accurate and concluded that “expert modification of fitted statistical models should be confined to species for which models are grossly in error, or for which insufficient data exist to construct solely statistical models”.

4.6. *Skroblin et al. (2019): an example of Indigenous Knowledge based Distribution models using Maxent*

Skroblin et al. (2019) aimed to assess whether Species Distribution Models (SDMs) including Indigenous Knowledge (IK) or field survey only data produced similar predictions on greater bilby (*Macrotis lagotis*) in Western Australia. Collected experiential wildlife knowledge included spatial information on where species may be present, perceptions on whether species distribution has changed, and where suitable habitats were. Data were collected through interviews and participatory mapping, whereby respondents would provide spatial information by annotating maps. Maps were then digitized in ArcGIS to create spatial polygons of occurrence. IK maps were converted to point data by sampling random points in the IK polygons to adjust IK into a format that could be used by Maxent to produce SDMs. Two Maxent models were run using IK and field-survey data, and were then evaluated using the area under the receiver operating curve (AUC) to assess model performance. They found that the AUC of the field-survey model was higher than that of the IK model and joint models, indicating higher performance, however it was indicated that the field-survey model may have overfitted data compared to the IK model. The predictive maps of habitat suitability differed among data types.

5. Discussion

5.1. *Search results*

This systematic literature search focused on key words related to knowledge holders, inclusion, wildlife populations/habitat use, and quantitative analysis to identify nearly 3000 candidate articles. Of these systematically identified articles, only 25 satisfied all eligibility criteria. Snowball sampling of articles that were cited by or cited these 25 identified an additional 24 eligible articles. Thus, the current systematic review is based on 49 primary literature articles incorporating local or expert knowledge into a quantitative analysis of terrestrial vertebrate populations or habitats. A potential limitation of our search string is the absence of taxa-specific terms (e.g., bird, waterfowl, goose, mammal, cat, leopard) or culture-specific terms (e.g., Maori, Maasai, Inuit, Cree) that may have been used by authors in place of more generic terms like “wildlife” or “Indigenous”. However, we did not include these to minimize the regional and species biases associated with their inclusion as it would be infeasible to include all appropriate terms for all taxa, regions, and cultures. Although snowball sampling of citing and cited articles identified additional articles missed in the systematic search, it remains likely we missed some eligible articles that omitted targeted search terms such as wildlife and Indigenous. A further limitation is our focus on peer-reviewed journal articles, which excludes reports, reviews, and project summaries published in other domains that may be more conducive to diverse knowledge inclusion in wildlife sciences.

The study locations, focal species, and knowledge holders identified through our review were inter-related, with the most common study species having high relevance and accessibility to the most common knowledge holders, and the most common knowledge holder type reflecting the most studied species and study areas. Although we identified that experiential wildlife knowledge has been included in quantitative analysis of wildlife populations and habitats across many parts of the world and across a wide diversity of terrestrial wildlife, we found that most articles were from the United States, Canada, and Australia, involved harvested birds and mammals, and most often solicited the knowledge of hunters and trappers. North America and Australia are regions from which there is generally high biodiversity research output (Trimble and van Aarde, 2012), meaning that these areas do not necessarily focus disproportionately on inclusion of experiential wildlife knowledge, and the high representation of academic experts in the review may be related to this. Indigenous Knowledge Holders were concentrated in Canada and Australia, and the inclusion of Indigenous or Aboriginal knowledge is consistent with the legal and social impetus in these countries for increased consultation and involvement in wildlife and natural resource management and research (Gilchrist et al., 2005; Lawrence and Macklem, 2000). Beyond these key regions, articles were globally distributed, including all continents except Antarctica. Thus, inclusion of experiential wildlife knowledge in wildlife science is a global phenomenon and has applicability in numerous regions worldwide (Brook and McLachlan, 2008). While a wide variety of taxa were studied, the most frequently studied species were game species or large charismatic carnivores. This could be attributed to the cultural and dietary importance of many genera in these taxa, particularly in the United States, Canada, and Australia (Titus et al., 2009; Hewitt, 2015; Krause and Robinson, 2021) where hunting is common and survey data is systematic and available (Arnett and Southwick, 2015; White et al., 2015; Sharp and Wollscheid, 2009). It could also be attributed to the high scientific and public interest in these species; of the most studied genera in the review which were represented more than three times across our articles, all are on a list of the 20 most charismatic taxa developed by Albert et al. (2018). Biases towards collecting more observational, person-based data on charismatic species dates back for centuries (Monsarrat and Kerley, 2018). There is also a high overlap between scientific and social interests regarding charismatic species (Jarić et al., 2019). Furthermore, familiarity with many of these large and charismatic species is high (Ulicsni et al., 2019) which could facilitate high levels of experiential wildlife knowledge in local and community knowledge holders.

5.2. Benefits

Benefits of including experiential wildlife knowledge in wildlife science that emerged across the review include experiential wildlife knowledge providing information that may be challenging or impossible to obtain through other data, increasing the rigor of models build on GPS collar, VHF, or field survey data, through guiding model development, providing context and improving interpretation of findings, decreasing costs of data collection, and increasing transferability of findings across long periods of collection (Table 1). We focused our analysis on the benefits that experiential wildlife knowledge provided to wildlife science and did not address benefits this process had to knowledge holders, because there was not enough information in the articles to extract and categorize those benefits. In some cases, knowledge holders provided information that would have been challenging or impossible to obtain through other means (Abram et al., 2015; Brook and McLachlan, 2009; Pearman-Gillman et al., 2020), particularly for rare or poorly documented species (Pearman-Gillman et al., 2020). Experiential wildlife knowledge was frequently discussed as a means to improve data-based models, with knowledge holder models providing the "backbone" for other models and making them more robust (Aycrigg et al., 2015; Brittain et al., 2020), improving or expanding upon other data (Brook and McLachlan, 2009), and identifying areas of weakness and guiding improvements in other models (Pearce et al., 2001). Experiential wildlife knowledge frequently identified new issues or areas of study, provided context, and improved understanding of model results beyond what would have been achieved without knowledge holder involvement (Brittain et al., 2020; Brook and McLachlan, 2009; Phommachanh et al., 2017). The comparatively low cost of experiential wildlife knowledge solicitation relative to other data collection was also discussed (Pearman-Gillman et al., 2020). Finally, the long time scales across which experiential wildlife knowledge is accumulated may offer additional advantages, including improved temporally transferability relative to models collected using single year data (Tuanmu et al., 2011) and the development of models more suited to future projection.

Table 1
Summarized benefits, limitations, and recommended improvements for interweaving local, expert and Indigenous wildlife knowledge into wildlife science.

Benefits
- Inherently recognizes the validity of diverse knowledge in science
- Increases knowledge holder diversity and trust in science and management
- Improves equity between scientists and other knowledge holders
- Provides additional information that improves or expands other data
- Useful for rare or under-studied species, with relatively low cost of acquisition
- Identifies points of consensus and disagreement as well as knowledge gaps
- Improves temporal transferability of models

Limitations
- May be exclusively local in scale
- May not be systematic in coverage
- Possible scale mismatches between different knowledge forms
- Interviewer and/or respondent reliability difficult to assess
- Potential biases introduced by interviewers and/or respondents
- Many wildlife scientists lack social sciences/qualitative methods training
- Communication/collaboration challenges due to differing knowledge priorities, language, worldview

Improvements
- Avoid assuming that quantitative data can be used to assess the reliability of other knowledge forms
- Use multiple statistical methods to assess congruence or disagreement between data sources
- Develop standardized methods to accommodate uncertainty and observer reliability
- Meaningfully include knowledge holders in more study phases, including study design and member checking
- Discuss intellectual property rights, knowledge ownership, and knowledge protection
- Acknowledge and discuss power differences between researchers and knowledge holders
- Assess and communicate knowledge holder benefits or negative outcomes in addition to science outcomes

5.3. Limitations

Common limitations to inclusion of experiential wildlife knowledge that emerged across the review were related to scale, reliability, bias, subjectivity, uncertainty, and author unfamiliarity with local knowledges (Table 1). Scale limitations include concerns including: experiential wildlife knowledge may be highly local in nature, it may be collected and applicable at a smaller scale than is desired for some projects (Doswald et al., 2007), and large regions of focus proved challenging to some experiential wildlife knowledge models in this review (Pearce et al., 2001). Other literature has discussed that experiential wildlife knowledge may not be systematic in coverage (Moller et al., 2004), and that Indigenous knowledge in particular does not resonate with the short temporal and large spatial scales at which most research or management projects are conducted (Wohling, 2009). Other authors contradicted this by arguing that experiential wildlife knowledge was well suited to large, particularly remote areas (Brittain et al., 2020; Pearman-Gillman et al., 2020). Many of the challenges of scale attributed to experiential wildlife knowledge may not reflect its own inherent limitations, but rather the mismatch of the scale of experiential wildlife knowledge with the scale of other data. For example, when habitat covariate data such as GIS layers are produced at a much broader scale than very local, experiential wildlife knowledge, utility is limited and using them both is a challenge (Bauder et al., 2021). Both interviewer and respondent reliability were identified as potentially problematic (Abram et al., 2015), and personal bias was described as impacting results and interpretation (Pearman-Gillman et al., 2020). The reliability of experiential wildlife knowledge depends critically on the knowledge elicitation method (Pearman-Gillman et al., 2020) and knowledge holder access to and familiarity with different parts of the study area. Another reliability challenge is that most ecologists interested in collecting and analysing experiential wildlife knowledge lack formal social science training, meaning they have limited experience interpreting and analysing qualitive information (Brook and McLachlan, 2005) and limited understanding of how to effectively account for identity, bias, and positionality in study design (Shank, 2002). Some authors believed that statistical methods could sufficiently accommodate the inherent subjectivity of experiential wildlife knowledge (Leblond et al., 2014), but others raised concerns that this might not be the case (Aylward et al., 2018). A final limitation we discuss here is a requirement of relevance and relatability between wildlife science objectives and available experiential wildlife knowledge, where wildlife science and experiential wildlife knowledge may lack common priorities or have major differences in worldviews. For example, knowledge holders may have different interpretations of taxonomy or levels at which species are distinguished (Berkes and Mackenzie, 1978; Newmaster et al., 2007; Phaka et al., 2019). Ziembicki et al. (2013) discussed that many species they intended to study had to be collapsed into larger groups or eliminated because knowledge holders did not differentiate some animals to the species level, or did not collect specific knowledge on some species where they had no cultural or dietary relevance. Experiential wildlife knowledge is likely to be strongest and most robust for species that are recognized and culturally important to knowledge holders (Brook and McLachlan, 2009; Ziembicki et al., 2013; Monsarrat and Kerley, 2018).

5.4. Comparison and assessment

Articles identified in this review frequently assessed the experiential wildlife knowledge models through comparison to independent, often quantitative, data sets, but this validation approach has been criticized and alternate methods to assess experiential wildlife knowledge should be considered. In their review of local knowledge inclusion in ecological literature, Brook and McLachlan (2005) discuss the tendency to use "*ecological data as a test to determine the reliability of Local Ecological Knowledge*". They argue that articles frequently fail to appropriately discuss the "assumptions, limitations, or constraints of the ecological articles that they use". Data such as telemetry locations or field-surveys introduces its own error, bias, and incomplete representation (Brook and McLachlan, 2005; Rykiel, 2001). For example, data that are limited in spatial and temporal scope may provide a de-contextualized snapshot of animal ecology with poor population-level inference (Hebblewhite and Haydon, 2010). Thus, it is becoming better recognized that independent data do not offer an opportunity to validate experiential wildlife knowledge, but that there is an opportunity to combine both forms of experiential wildlife knowledge in a manner that advances understanding of the ecological system and each source of information (Polfus et al., 2014). Indigenous experiential wildlife knowledge in particular arises from distinct worldviews and ways of understanding ecosystems and wildlife relative to those involved in the design and collection of data (Bohensky and Maru, 2011). Difficulties with Indigenous knowledge inclusion in particular can be addressed through "*reframing integration as a process in which the originality and core identity of each individual knowledge system remains valuable in itself, and is not diluted through its combination with other types of knowledge*" (Bohensky and Maru, 2011). Methods such as "two-eyed seeing" (Reid et al., 2020) are increasing in use and may help to achieve this goal.

5.5. Improvements

Experiential wildlife knowledge inclusion in quantitative analyses can be further improved in future works through multi-model inference, better accounting of variation, bias, and uncertainty of experiential wildlife knowledge, engagement of knowledge holders in multiple study phases, and further consideration of intellectual property rights and power dynamics of experiential wildlife knowledge and policy (Table 1). Comparing the success of different models is challenging when each article applies a single statistical method to a unique study area, focal species, knowledge holder category, and experiential wildlife knowledge type. Future works may benefit from performing several statistical models on the same set of observations to assess how model selection impacts success of experiential wildlife knowledge integration (Polfus et al., 2014). Furthermore, additional work to develop standardized techniques for accommodating expert uncertainty may be beneficial. Many authors addressed uncertainty, and challenges with quantifying bias and variation in responses as a primary concern. Another area that future studies can improve upon is knowledge holder engagement in earlier and later phases of the research process and, if this occurs, clearer presentation of the form and outcomes of these engagements in research articles. Few articles discussed whether knowledge holders were involved in the co-design of study approaches and knowledge elicitation methods and few described member-checking or results dissemination after local knowledge was collected. While many authors communicated satisfaction with results of the knowledge integration process, the lack of member checking or follow-up interviews makes it challenging to verify if the knowledge holders shared their assessment. Brook and McLachlan (2005) state that "*if local knowledge is to be used in a respectful way that recognises its inherent and use-value, community members should be meaningfully involved in most, if not all, aspects of a study*". Finally, more discussion of the intellectual property rights, knowledge ownership, and control over the resulting data is warranted (Brook and McLachlan, 2005). For experiential wildlife knowledge inclusion to be effective, co-management and research requires equitable partnerships and sharing of information and power (Popp et al., 2019).

6. Conclusion and implications

Through this review, we aim to provide a resource for future research teams from which to begin designing projects that meaningfully include experiential wildlife knowledge into analysis. By reporting all categories and sub-categories of methodologies found in articles, we provide a portfolio from which researchers may observe a plethora of options and select the most suitable methods or strategies. Our case studies may also provide a brief framework from which to begin planning or brainstorming a future study design, while also informing readers of the authors self-reported assessment of success using such methods. By doing this, we hope to assist teams already incorporating experiential wildlife knowledge by exploring and presenting other options, and to assist teams just beginning to consider this valuable area of science or work with knowledge holders by providing a toolbox of resources and references for consideration. The growing publication output of experiential wildlife knowledge in wildlife science may benefit both scientists and knowledge holders by increasing communication, engagement, and trust. It may also benefit scientific rigor and application by increasing contextual understanding of data and results and increasing or improving data with which to conduct analyses. By meaningfully including experiential wildlife knowledge, there is the potential to develop methods of more inclusive science that benefits scientists, knowledge holders, and wildlife.

Declaration of competing interest

We declare no conflicts of interest.

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Appendix A. Supplementary data

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