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ORIGINAL ARTICLE

Turning biodiversity data into evidence: the role of protocols in the epistemology of evidence-based conservation

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Abstract

Proponents of evidence-based conservation (EBC) maintain that environmental intervention ought to be based on biodiversity data and data synthesis, instead of relying on unproven theory, individual expertise, and customary practices. This paper analyzes the epistemology of EBC, in which data are bestowed, explicitly or implicitly, with a privileged status and intrinsic evidential significance. I problematize this view by reviewing the complex knowledge infrastructure and dynamics involved in *turning* data into evidence within biodiversity conservation. Building on the philosophical literature on the nature, journey, and social embeddedness of data, I highlight the critical role of scientific *protocols* in producing reliable, actionable knowledge for conservation. I argue that protocols are established precisely because data do not have the highest epistemic privilege or intrinsic evidential significance. To illustrate my point, I examine two case studies: the Conservation Evidence project and the Red List of Threatened Species. I discuss some of the conceptual and practical consequences of improving the epistemology of EBC. Furthermore, I show how protocol implementation can generate multiple data communities that are constrained by, yet open to, negotiations regarding evidential standards.

Keywords Evidence-based conservation · Evidence · Data · Protocols · Data communities

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Introduction

Big data has often been heralded as a new paradigm for knowledge production in the natural and social sciences (Stephens et al. 2015). Some have described big data as the "new oil" and compared it to innovations such as the telescope and the microscope in astronomy and biology (Hilbert 2016). The unparalleled volume, value, variety, velocity, and accuracy of information available today are frequently praised for their potential to provide a more extensive and diverse body of evidence for testing hypotheses and validating knowledge about natural and social phenomena. This, in turn, is expected to result in improved interventions compared to conventional knowledge-production methods, which are often characterized as circumscribed, opaque, homogeneous, and potentially biased by human actors. This paradigm, while adopted at different speeds across disciplines, has permeated nearly all scientific domains (Vydra & Klievink 2019). In ecology and biodiversity science—the focus of this paper—leveraging large datasets is widely seen as essential for addressing the ongoing biodiversity crisis. Big data is regarded as the key to producing synthesis studies, which integrate diverse datasets to reveal complex ecological and environmental patterns and interactions (Hampton et al. 2013). Big data and big data technologies are also gaining momentum in conservation through advancements such as environmental DNA (eDNA) analysis and next-generation tools for population genetic studies and biodiversity assessments (M. E. Hunter et al. 2018).

This optimistic attitude toward big data is especially pronounced in evidence-based approaches to conservation. Proponents of evidence-based conservation (EBC) argue that environmental action should be justified by sound ecological knowledge derived from extensive and comprehensive empirical data, rather than relying on circumstantial observations or individual expertise, as was common in the recent past. EBC has a data-centric epistemology that occasionally results in conflating the notions of "data" and "evidence."

This paper examines knowledge production in biodiversity science in relation to the epistemic assumptions central to EBC, arguing that data should not be treated as evidence: they must be *turned into* evidence (Smith 2014). The paper proceeds as follows.

Section "Evidence-Based Conservation" introduces EBC and its underlying epistemology, structured around three assumptions: (1) the epistemic privilege of data; (2) that "the bigger the data, the better the evidence"; and (3) the conflation of "data" and "evidence". Section "Mirror View of Data embedded in EBC" links these assumptions to a lingering, often unstated, "mirror view" of data. Section "Turning data into evidence" reviews philosophical accounts of how evidence is painstakingly extracted from data, focusing on the nature of data and their context of use and interpretation. These accounts challenge the mirror view and interrogate the epistemic assumptions characterizing EBC. Section "Protocols and knowledge production" introduces a complementary dimension: the role of scientific *protocols* in turning data into evidence. Protocols structure knowledge production into discrete, transparent, and justifiable steps. Crucially, their implementation is necessary because data do not have the epistemic function attributed to them. I examine two cases—Conservation Evidence and the Red List of Threatened Species (Subsect. "The Conservation Evidence Project" and "The Red List of Threatened Species")—to show how protocols validate actionable knowledge. Section "Conceptual and Practical Consequences" outlines the conceptual and practical implications of revising the epistemology of EBC. Finally, Sect. "Protocols and Knowledge Production" shows how protocol implementation gives rise to "data communities," which transform data into evidence through dynamic, sequential processes.

Relations between data and evidence are central to investigating the epistemology and the methodological dimensions of science. Combining philo-sophical analysis with an examination of online resources and institutional practices, I contribute to the broad debate as to what "evidence" means in evidence-based approaches (Cartwright & Stegenga (2011), to the conversation around the role of protocols in science and policy (Tsiroukis, MS) and in the making and working of data communities (Bocchi, Cavazzoni, & Castano, Special Issue). I also engage more specifically with some of the hidden assumptions and desiderata underlying evidence-based conservation, offering a more realistic and careful representation of the epistemic authority of scientific knowledge and how evidence is operationalized.

Evidence-based conservation

Amidst a severe environmental crisis, what policies and strategies work, and how do we know it? Inspired by developments in medicine, conservationists over the last two decades have increasingly responded to this question with a call for an evidence-based approach to safeguard biodiversity and manage natural resources (Sutherland et al. 2004; Pullin et al. 2004). Biodiversity conservation has traditionally relied on intervention methods whose scientific rigor and effectiveness have gone largely unchecked (Downey et al. 2021; Rafidimanantsoa et al. 2018; Pullin et al. 2004). In fact, "intuition", "anecdotes", and "myth" have been documented to outweigh scientific literature in guiding practices and policies (Sutherland et al. 2004). This issue persists to some extent today: recent reviews indicate that conservation interventions often receive support and funding, despite a lack of empirical evidence for their effectiveness (Pullin et al. 2004; S. B. Hunter et al. 2021; Al-Fulaij et al. 2025).[1]

EBC takes issue not only with what proponents see as weakly justified conservation *interventions*, but also with the basic *ecological hypotheses* upon which these strategies are conceived. For example, the hypothesis that there is a nexus between local biodiversity decline and loss of ecosystem function (Vellend 2017), or that habitat fragmentation is detrimental to evolution and taxonomic diversity (Fahrig 2017; Schilthuizen 2018) are common assumptions in designing conservation strategies. Yet they are inadequately supported by evidence, according to some EBC advocates. Similarly, the diversity stability hypothesis or the hypothesis that migration patterns follow climate change, are part of the knowledge toolkit of conservation planning,

[1] Advocates of evidence-based conservation continue to express frustration with this unfortunate disconnect between funded projects and the state of the evidence (Carrier & Nordmann, 2011; Ferraro & Pattanayak 2006). For example, bridges, gantries, or underpasses intended to make roads safer for animals and drivers have proven ineffective in preventing collisions among bats, birds, and drivers (Berthinussen & Altringham 2012). However, their installment is still encouraged and funded (Downey et al. 2021).

"treasured tenets" (Kareiva et al. 2018, p.vii), despite inconclusive or even disproving evidence.

To counteract this trend, evidence-based approaches emphasize the importance of grounding action in reliable ecological knowledge and demonstrable evidence of effectiveness. But how is such reliable ecological knowledge and confidence in the effectiveness of the intervention established? I will demonstrate that the epistemology of EBC rests on three intertwined hidden assumptions: (1) data are epistemically privileged; (2) more data mean better evidence; and (3) data are, after all, the evidence.

(1) The epistemic privilege of data EBC bestows what we may call an "epistemic privilege" on data: the view that data are the decisive factor in ascertaining the validity of knowledge claims and the success of conservation actions. Since the production of reliable and actionable knowledge requires a complex *infrastructure* of elements and actors—including models, methods, social groups, individual expertise, technologies—bestowing epistemic privilege on data is not an obvious move but one that rests on a series of commitments as to what counts as and what grounds knowledge, often left implicit.

The epistemic privilege of data clearly emerges in both formal texts and informal discourse. A telling example is the edited volume "Effective Conservation Science: Data Not Dogma," edited by prominent EBC advocates Peter Kareiva, Michelle Marvier, and Brian Silliman. The title itself, which opposes dogma to data, signals a shift of epistemic authority: from custom ("dogma") to field and experimental observations ("data"). The editors frame the book around the shared assumption that data have often been ignored in favor of "expert opinion and black box models" in environmental decision-making (Kareiva et al. 2018, p.5). This is epistemically problematic, they contend, as conservation progress "only because new data and analyses vanquish old ideas and assumptions," (p.vii) and even the validation of customary methods depends on "dig[ging] deep into the data" (p.viii). The book is framed explicitly as an exemplary collection of "stories of conservation scientists following the data—to wherever it may lead" (p.viii), urging the adoption of a mindset: that "the single most important principle should be to follow the data" (p.viii).

The epistemological commitment to the privilege of data is echoed in several of the contributions. For example, McClellan and Davies argue that "Our environmental decisions are derived from the data we use: if we want evidence-based decisions, we need evidence that is clear and transparent." (McClellan & Davies 2017, p.15). They rightly denounce the scientific and managerial tendency to reduce natural complexity to aggregate indicators and simple metrics and rely on these unproblematically in both scientific publications and policymaking. However, they warn that "we should prefer actual measurements" to numerical values resulting from the aggregation of these data in environmental and sustainability indices and indicators.[2] If the usage of these tools is inevitable, "their underlying data must be available, traceable, and transparent" (p.11). Their diagnosis is that environmental indices are treated as raw data instead as models (p. 14). With this, they reiterate the epistemic stance that data,

[2] Cfr Bocchi 2024b for a philosophical critique.

especially in their original, raw form, are epistemically privileged in knowledge production and action.

A similar logic underpins a rather different contribution by ecologist David Skelly (2017), who draws attention to the central epistemic and normative role of natural history data. While acknowledging the vital role of "experiments, models, surveys, global assessments, and meta-analyses" (p. 88), Skelly asserts the fundamental epistemic value of archival materials such as museum records and specimen collections and field-based observations in providing a complex, detailed, and actionable picture of the world. Despite being dismissed as a "weak form of inference" in the publishing industry, EBC should really emphasize their epistemic value; otherwise it risks becoming an abstract and technocratic exercise. Once again, Skelly implicitly vouches for the privilege of (a very specific type of) data as foundational to the EBC machinery.

(2) The bigger the data, the better the evidence The epistemic privilege granted to data in EBC explains the common belief that an increase in data yields superior evidence. Emphasis on data collection and sharing, and the appeal to evidence synthesis are loci for the enactment of this stance. I will use the rather flamboyant slogan "the bigger the data, the better the evidence" to capture a set of desiderata and practices underpinning EBC: that the more data almost automatically entails improved evidence.

The underlying existence of this slogan is evident in EBC's emphasis on the need for more data, improved data collection and sharing technologies, and better-curated data infrastructures. At the core of EBC is the stance that collecting and compiling biodiversity data can overcome the epistemological limitations of traditional conservation, particularly its exclusive reliance on limited information and anecdotal knowledge. Data are made available via remote sensing tools that record species distributions and densities from above in the form of images, videos, and thermal signatures (Kelling et al. 2009). Camera traps, environmental sensors, transmitting collars, and other tracking devices monitor species on the ground or in the oceans. Citizen science platforms such as iNaturalist and eBird contribute further with millions of geo-tagged records about species presence and distribution, and are regularly cited in scientific publications (McKinley et al. 2017). eDNA samples, herbarium and zoological records, and museum collections provide additional data. These are only some of the many sources and types of biodiversity data upon which conservationists optimistically look to ground what they see as reliable and actionable ecological knowledge, and as the basis of conservation efforts.

Bringing attention to the "the bigger the data, the better the evidence" slogan also helps understand why data scarcity is often charged with being a, if not *the*, major barrier to conservation. The problem of missing or scarce biodiversity data affects every step of scientific knowledge production, from data collection (Turner et al. 2015), data sharing (Hampton et al. 2013, Gregoire, Derderian, & Le Lorier, 1995, Konno et al. 2020), data reuse (Zimmerman 2008). In conservation, data scarcity is common due to the complex and diverse nature of ecological systems, the absence of long-term studies, and inadequate reporting of research findings (Bayraktarov et al. 2019). Insufficient data are sometimes held as the main reason for misplaced resource allocation or failed conservation strategies (Stuart, Wilson, McNeely, Mittermeier, & Rodrıguez, 2010).

The accessibility of a large amount of biodiversity data has enabled the development of sophisticated analytical and machine learning techniques. However, the most prominent epistemological move in EBC is not technical but methodological: the call for evidence synthesis. Evidence synthesis is a family of methods that includes meta-analyses (Gurevitch et al. 2018), literature reviews (Barry et al. 2022), and systematic mapping (Sutherland & Wordley 2018) that aim to combine disparate sources of knowledge to explain biodiversity patterns and to guide policy. Crucially, evidence synthesis depends on the availability and aggregation of large quantities of data. The assumption is that bigger data enable stronger evidential claims: larger datasets improve statistical power, support generalizations, and potentially reveal patterns that would not be visible in small-scale studies or traditional field ecology. In other words, data volume is a proxy for evidential strength.

In this view, bigger data ground the epistemic authority of EBC methods compared to traditional approaches. The entire evidence synthesis machinery emerges from the logic that since data are bestowed privileged epistemic status, then data synthesis yields better actionable knowledge. More or less implicit support for this view is found in the pioneering paper by William J. Sutherland, Andrew S. Pullin, Paul M. Dolman and Teri M. Knight "The need for evidence-based conservation" (2004) that introduced the idea of evidence synthesis in conservation. Sutherland's and colleagues' contribution to the advancement and spread of EBC is immense, as well as the robustness and utility of evidence synthesis (Sutherland & Wordley 2018). Yet, this foundational paper illustrates how the epistemology of EBC is implicitly imbued with the idea that "the bigger the data, the better the evidence". To begin with, the paper praises the evidence-based approach to medicine (EBM) for its commitment to ground actionable knowledge on voluminous and heterogeneous data, rather than focusing on methodological rigor *per* se.[3] In the article, the real problem with effective conservation is identified in that

> each individual only has limited experience of the outcome of an intervention. Each of these experiences can be thought of as a single data point. The experience of each individual is minuscule compared with the total experience of all practitioners. (p.306).

The diagnosis here is simple: individual and anecdotal experience (aka the epistemic ground for traditional conservation) are limited and biased, a problem that more data could solve while guiding towards better knowledge. I am not suggesting that EBC proponents underestimate the epistemic value of rigorous methods for synthesis, yet their framing suggests that the core epistemic leverage is performed by big biodiversity data.

(3) Data equal evidence So, how do you tell if there is evidence for the effectiveness of an intervention? Primarily, if you have data. If more data means better

[3] Celebrating EBM for its methods would be risky: reliance on meta-analysis in EBM has been the subject of great controversy. See Stegenga (2011) and Goldenberg (2011) for a philosophical critique.

evidence for reliable and actionable knowledge, then data are *effectively treated as* evidence in the epistemology of EBC. In fact, data and evidence are occasionally used interchangeably in the literature and casual conversation, and the distinction between the two is sometimes collapsed altogether. This is also true in programmatic reflections on what counts as evidence within the field.

For example, in a sophisticated theoretical contribution to the EBC literature, Nick Salafsky et al. (2019) discuss how to conceptualize "evidence" and "evidence thresholds" in conservation decision-making. To this end, they invoke the classic Data-Information-Knowledge-Wisdom (DIKW) pyramid (Ackoff, 1989), using it to frame what determines whether a knowledge claim is substantiated by evidence. The pyramid describes the hierarchical foundation of cognitive activities (information, knowledge, and eventually wisdom) as grounded in data—the bottom level. While the authors acknowledge that "adjudicating whether there's enough evidence for a hypothesis" depends both on how well-formulated and testable the hypothesis is, and on the quality of analytical methods, they ultimately ground the authority of all these evaluative processes in the evidential capacity of empirical data. In other words, even synthesis methods and meta-analyses derive their epistemic weight from the input data. Indeed, they explicitly report a consensus view that

> In the end, the collective weight of an overall evidence base is a function of the weight of the individual sources and the manner in which they were assembled, screened, and assessed.

Even acknowledging that compilation, analysis, and verification are an integral part of EBC workflows and must be rigorous and transparent, the epistemic strength of evidence is still widely seen as a function of both the quality and quantity of data. As a result, the answer to the question: 'Do you have evidence?' could simply be: 'Indeed, I have data!'.

To summarize: The epistemology of EBC is heavily data-centered. Data hold an epistemic privilege, as they are regarded as the ultimate difference- makers in validating knowledge and justifying conservation efforts. When EBC proponents suggest that conservation decisions should be evidence-based, what they mean in practice is that more data are needed, where gathering data almost inherently equates to acquiring more evidence. Collecting and disseminating environmental data appears to be a promising way to ratify ecological knowledge claims or dispose of mistaken ecological hypotheses. The discourse on evidence is largely built upon data, to the extent that the two concepts sometimes overlap.

Mirror view of data embedded in EBC

The epistemological assumptions of EBC are better explained with reference to a specific and not uncommon view of the nature of data, one that portrays data as uncooked, factual, and neutral epistemic elements—the "stuff of truth itself" (Gitelman 2013). Within this conception, data have been said to "speak for themselves" and provide a "view from nowhere" (Rieder & Simon 2016), purportedly minimizing expert-centered or theory-laden knowledge (Anderson 2008). To those who endorse this view in biodiversity science, ecological patterns are "born from the data" (Kelling et al. 2009, p. 613), where data shield scientific inference from the distorting influence of theories, values, or bias. Data can speak for themselves by virtue of an inherent *factuality*, or "givenness" that counterbalances the perceived uncertainty of relying on expert judgment (Rieder & Simon 2016; Porter 2020).

I suggest that the epistemology of EBC can be better understood in relation to this underlying view of data and their emerging epistemic features Philosophers of science have labeled this view the "mirror view of data." This ontological stance holds data to be "an unmediated window onto the world, whose epistemic reliability is given" (Bokulich & Parker 2021, p.31). Data are unproblematically claimed to be a "given," a faithful *depiction* (sensu Bokulich 2021), or a direct presentation of the world, unlike theories and hypotheses, which are considered mediated and biased by human cognitive limitations. In virtue of this presentational capacity, data are attributed intrinsic *evidential* significance—they are the direct evidence for explaining or predicting scientific phenomena.[4]

I propose that the epistemology of EBC is not immune to this ontological stance. My argument is grounded in an inference to the best explanation (IBE): the commitment to a mirror view helps make sense of the three assumptions identified above.[5]

First, the assumption that data have epistemic privilege can mask the endorsement of the mirror view. If data directly depict ecological phenomena, they must be closer to nature and thus more reliable than epistemic tools such as theories, models, or expert judgments.[6] Their directness, immediacy, and unbiasedness serve as a warrant for their status at the top of the epistemic hierarchy. Second, if data hold this high epistemic status, then it is trivially true that data accumulation automatically leads to better evidence for ecological knowledge claims. Data abundance is a proxy for better evidence, while analytical methods like evidence synthesis gain value primarily as aggregation instruments. From this perspective, maximizing data availability appears epistemically necessary. Third, if biodiversity data are direct windows to ecological phenomena, then they must carry intrinsic value *as evidence*—not because of how they are manipulated, but because of what they are presumed to mirror. This makes them the ultimate evidence upon which knowledge rests, sometimes leading to declarations where the boundaries between data and evidence are blurred, if not collapsed altogether.

Despite being deeply problematic, as I will argue next, this ontological view seems to linger under the general scientific and managerial optimism and trust placed in data, possibly including the epistemology of EBC. Giving up on the mirror view opens the door to formulating a more realistic and responsible epistemology, as I

[4] Thinking of data as given is consistent with the idea that evidence itself has a factual character. As Goldenberg (2006) claimed, focusing on the notion of evidence at the heart of evidence-based medicine, "the notion that any claim (including scientific beliefs) can stand or fall in light of the evidence assumes a'givenness' of evidence as'facts' about the world" [p. 2623].

[5] A similar argumentative strategy is used by Zhao (2023), who employs IBE to link psychometric measurement practices to an implicit realist ontology, even when this com- mitment is not explicitly stated. See Bocchi 2024a for a more explicit connection between this argumentative strategy and conceptual disagreement within biodiversity conservation.

[6] For a criticism and a more nuanced view on expert judgment, see (Majszak & Jebeile,2023)

argue in Sect. "Conceptual and Practical Consequences". Ultimately, my critical assessment of the ontological and epistemic assumptions underneath EBC invites a re-evaluation of what is required to talk about evidence-based action, as well as the practices stemming out from this theoretical scaffolding.

Turning data into evidence

Few would argue that conservation should not be based on evidence, where evidence is understood as a genuine warrant for endorsing ecological hypotheses or relevant environmental action.[7] However, what one means by "evidence" determines what one takes the foundation for science-informed interventions to be.

In this section, I provide a brief review of some philosophical work that challenges the epistemology and the ontological assumptions underpinning EBC discourse. I focus on prominent criticisms of data's alleged givenness, intrinsic evidential significance, epistemic privilege in knowledge production and science-based interventions—focusing on at least two major fronts.

Firstly, philosophers have unpacked the nature and journey of data, demonstrating that the assumption that "data can speak for themselves" is flawed. Data are not simply given; they are made (Leonelli 2016).The nature of data is better conceptualized as *relational* (Leonelli 2016) or *pragmatic* (Bokulich & Parker 2021) rather than purely presentational. Scientists must "fight for" data that are relevant to their purpose (Kuhn 1961) as "raw data" do not themselves establish solid knowledge. Instead, they must be transformed—moved, manipulated, polished, analyzed, and repurposed—to become evidence. In the process of knowledge production, data require modeling, infrastructures, and established norms to be usable and reusable. Infact, data do not even need to be accurate or precise representations of reality to contribute to knowledge; instead, they must be "good enough" or "adequate" for a specific purpose (Parker 2020; Watkins 2024).

Philosophers have shown how practices such as "data packaging" prepare data for their journey across research communities, shaping their evidential scope. For instance, data must often be turned into data models (Bokulich 2020) or derivative datasets, such as mathematical sequences, to enhance their usability in predictive and descriptive models (Tempini 2020). Other practices—such as data decontextualization through standardization (Leonelli 2016) and their subsequent recontextualization—allow them to be reused across multiple research contexts (Lloyd et al. 2022, p.807).

The diachronic life of data—their journey from collection to use in knowledge claims, also known as "data lineage" (Leonelli 2020) or "data phylogeny"(Bokulich & Parker 2021)—further demonstrates how contextual elements expand or shrink their evidential significance. Among these contextual elements, meta-data ("data

[7] "Evidence" has been a major topic in philosophy of science. A major philosophical trend in the relationship between data and evidence involves formal accounts within theory or hypothesis confirmation (e.g. Mayo 2018; Sober 2015. Another major trend focuses on the nature and usage of data in scientific practice (e.g., Leonelli 2016; Bokulich & Parker 2021. My analysis builds on this second trend.

about data") play a crucial role. Metadata encompass qualitative information about collection tools, calibration rules, and even the attitudes of data collectors (Liboiron 2021). Metadata constrain and "enrich" the evidential scope of data, impacting the evidential landscape they can contribute to (Boyd 2018). Moreover, the material and local characteristics of data (Wylie 2017; Chapman & Wylie 2018), researchers' creativity and economic resources to move or store them can limit their portability and evidential significance.

Secondly, going beyond the nature of data itself, the evidential value of data is shaped by background assumptions, social contexts, and theoretical frameworks. The same data can support multiple, potentially conflicting knowledge claims depending on the sociocultural and theoretical assumptions underlying their interpretation. For example, the same artifact can be used as evidence for different reconstructions of past social dynamics depending on accepted sociocultural assumptions (Wylie 2015). Accepted midrange theories establishing regularities between events (Jeffares 2008) or technological machinery further affect the inferential warrant of data (Currie 2018; Wylie 2017; Chapman & Wylie 2018).

Decades of feminist scholarship against a "view from nowhere" about what counts as evidence contradicts the tale that data have intrinsic evidential power. Feminist epistemology critiques have exposed the unrealistic assumption that the positionality of epistemic agents does not affect scientific knowledge. Knowledge production unfolds in a socio-scientific milieu where researchers are historical agents, and it is thus not data alone that determine which scientific hypotheses are accepted as evidenced. Accordingly, evidence is always context- and knower-dependent (Longino 1990; Code 2012), and belongs to a social system in constant change (Goldenberg 2006). On the normative side, blindly adhering to what is deemed incontrovertible scientific evidence also carries the risk of perpetuating oppressive social dynamics (Oreskes 2021).[8]

The philosophical perspectives examined here underscore the limitations of an epistemology that treats knowledge production as grounded on the givenness and privilege of data, and that sometimes equates data with evidence. Instead, the relational, context-dependent nature of data and the socially constructed standards for their interpretation demonstrate that knowledge production requires data to be turned into evidence through manipulations and technologies, only valid within a socio-historic and dynamic evaluative framework. Revealing the nature of data, their journey, and the social standards for deeming data as evidence is an essential, albeit unfinished, phase in revising EBC epistemology.

[8] Consider, for instance, the feminist critique of the scientific community's delayed acknowledgment that birth control has harmful side effects. Patient reports and doctors' notes were treated as "anecdotal" by the scientific community until corroborated by large-scale data studies decades later (Seaman 1995). This differential treatment of patients and big clinical data is due to the different values endorsed by the scientific community.

Protocols and knowledge production

As explained in the previous section, philosophers of science have effectively challenged bold claims about the epistemic privilege of data in knowledge production, the reliance on their abundance to warrant actionable knowledge, and their intrinsic evidential power, developing their critical accounts at scales of either high or low granularity. At one end, accounts such as Leonelli (2016) Bokulich and Parker (2021), and Boyd (2018) zoom in on the fine-grained aspects of data manipulation and transformation to turn data into evidence. At the other end, Longino (1990) zooms out to analyze the broader societal and ideological contexts that determine evidential standards within socio-political environments. In this section, I aim to highlight an important but under-theorized dimension of knowledge production that occupies a middle ground: protocols.[9]

I understand protocols as organizational features of research environments whose analysis is irreducible to the details of data journeys, as it requires broader group-specific norms that might not emerge from the study of the nature and life cycle of data and data technologies. At the same time, the norms involved in protocols for knowledge production pertain to research collectives without primarily relying on overarching socio-cultural frameworks or ideologies. This is why I consider protocols to operate at an "intermediate granularity," providing a unique perspective on knowledge production that illuminates underappreciated aspects in the epistemology of EBC.[10]

Protocols in biodiversity science and conservation are common; they are standardized, step-by-step procedures that ensure actions are carried out correctly.[11] Examples of protocols especially relevant in the conservation context include obtaining ethical approval for resource sampling, standard procedures of data collection, and a journal peer-review process. While this paper does not attempt to survey or categorize protocols exhaustively, I focus on two high-profile cases that exemplify their role in facilitating the process of turning data into evidence within biodiversity conservation.

[9] Within the constructivist tradition in sociology and STS, protocols have received explicit attention as central tools in knowledge production. Laboratory and biological research have been key sites of analysis, where protocols appear as standardized practices that ensure comparability and reproducibility, while remaining flexible enough to accommodate individual expertise and context (Latour & Woolgar 2013; Knorr-Cetina 1981; Lynch 2002). More recently, their establishment and evolution have received more explicit attention, often as easy procedures for data accumulation (McLellan 2021) and as invisible organizational tools, until failure (Rao 2023). Closer to the approach of this paper, Schmidt (2024) analyzes protocols as tools for epistemic coordination among diverse actors (what I will later call 'data communities'), institutionalizing trust in the steps of knowledge production and delimiting the space for negotiating evidential standards.

[10] Both types of analysis that have received significant philosophical attention can involve protocols. In a sense, thus, philosophers of data have not ignored protocols, but an explicit focus on their epistemic status and authority is still relatively unexplored, with some exceptions such as in philosophical research on replication and meta-analysis (eg. Kovaka 2022; Stegenga 2011).

[11] Even when the steps of a protocol are well-documented and thoroughly reported, full transparency is not guaranteed [Bocchi & Santana, MS].

The Conservation Evidence project

The first case I will discuss stems directly from the early-2000s quest to introduce evidence-based methods into conservation and to assess whether particular interventions are effective. One of the major issues for conservation to work is the scarcity and poor circulation of information among ecologists and data availability for conservationist practitioners (Reichman et al. 2011; Tedersoo et al. 2021). Prominent ecologist William Sutherland, whom we encountered in Sect. "Evidence-Based Conservation", saw a solution to this problem: building a centralized digital database to "include information from any level, from randomized, replicated and controlled experiments to the response to a single uncontrolled intervention" (Sutherland et al. 2004, p.307).

The Evidence Conservation project, based in Cambridge (UK), serves as a publicly accessible archive housing (as of today) around 8000 interventions to be assessed for effectiveness. The project collects token studies of conservation interventions, classifies them into types, and assesses them based on six effectiveness labels: "Beneficial", "Likely to be beneficial", "Trade-offs between benefits & harms", "Unknown effectiveness", "Unlikely to be beneficial", "Likely to be ineffective or harmful". For example, planting nectar flower mixtures or wildflower strips has been assessed as beneficial upon scrutiny of as many as 104 studies. Reducing tillage is labeled "likely to be beneficial" with an analysis of 46 studies, while planting or maintaining ground cover in orchards or vineyards was assessed as "Likely to be ineffective or harmful" with 14 studies. This project is well integrated into the conservation landscape, having partnered with thousands of initiatives and received awards for its efforts to ground conservation in sound science.

How is each assessment for the effectiveness of conservation intervention produced? The project relies on a protocol through which available studies are summarized and the epistemic legitimacy of the assessment is established. The protocol comprises three steps, which are detailed in written and video form on the Conservation Evidence website and in their main publication (Sutherland, Dicks, Petrovan, & Smith, 2021):[12] Here is a breakdown of the protocol.

Step 1: Production of an Individual study report The assessment begins with the EBC group producing a 150–200 word summary of a scientific study documenting a conservation intervention, including the study's context and its quantified consequences. So far, hundreds of studies have been summarized through literature searches within journals and grey literature, and their results reported according statistical thresholds of significance. Each study has a dedicated page linked to other token studies testing the same conservation intervention. Studies without quantitative data on the intervention's result are not considered.

Step 2: Creation of Synopsis Once several individual studies have been summarized, they are included in a synopsis. A synopsis is a collection of studies understood as tokens of the same type of intervention aimed at conserving a species group or habitat or tackling a specific issue. Synopses pull studies together but do not include an effectiveness assessment. Each synopsis is produced by an advisory board that

[12] Videos are available here: https://www.conservationevidence.com/content/page/89

includes members of the Conservation Evidence Project and external consultants specializing in the area under scrutiny. The method used is subject-wide evidence synthesis rather than a systematic review, which serves as a cost-effective approach for evidence synthesis. The advisory board members are trained in this method. Each protocol followed when compiling an individual synopsis is registered on the Open Science Framework website and then published online.

Step 3: Expert Elicitation The Conservation Evidence project distrusts individual expert judgment. The attribution of one of the six assessment categories is done by a panel of experts whose judgment is elicited through a modified Delphi technique, considered a transparent, repeatable, and inclusive judgment aggregation method (Mukherjee et al. 2015). In a step-by-step process, experts who did not take part in Steps 1 and 2 are asked to state their opinion about the effectiveness of a specific intervention. Experts are provided with a synopsis, and their judgments are anonymously collected. Additionally, they are required to document their confidence level in their judgment. Whether each intervention type is beneficial for conservation is determined by calculating the median of all experts' effectiveness assessments, combined with their self-rated certainty. The panel members can openly object after reviewing a summary of scores and comments from the rest of the panel based on their own experience and individual knowledge. After objections, the panel may be asked to repeat the process. The final scores are then collected, and the individual assessment is ratified.

The Red list of Threatened Species

A second case of protocol for knowledge production is the one employed to compile the Red List of Threatened Species ("Red List" henceforth), a collection of global and regional extinction risk assessments for animals, plants, and fungi that leverages sheer quantities of data to inform conservation policy-making.

The Red List is a conservation initiative within the International Union for Conservation of Nature (IUCN) with high political and scientific standing, providing authoritative knowledge about extinction risk across taxonomic groups. The attempt to measure extinction pressure on species has a long and controversial history (Mace et al. 2008). It took forty years of discussion to agree on a robust method, which includes a general, regimented protocol called "redlisting" (Fitter 1987; Mace & Lande 1991). This protocol is set to generate an assessment of species' extinction risk by attributing one of six extinction risk labels—"Extinct", "Extinct in the wild", "Critically Endangered", "Endangered", "Vulnerable", "Least Concern"—to species for which enough data are available. Species' extinction risk assessment involves a four-step protocol:[13]

Step 1: Pre-Assessment Stage Redlisting begins with IUCN members or independent collaborators collecting all available data about the species under evaluation, including grey literature and unpublished works (Bachman et al. 2019). This stage

[13] I took the IUCN Red List Assessor Training Course (conservationtraining.org) to grasp the details of how extinction risk assessment is performed, including how diversity data are collected, analyzed, interpreted, reviewed, and published.

involves compiling a draft range map, which visually represents the species' distribution based on observational or inferred data. These maps, while approximate, help identify potential overlap with extinction risk factors (Hurlbert & Jetz 2007) and can be used to justify the assessment. The collected data are stored in the Species Information Service (SIS) database, ensuring standardization and facilitating collaboration among researchers.

Step 2: Assessment Stage Once the data have been made available, a second group of experts conducts the central phase of the assessment, resulting in the attribution of a risk category to the species. This phase often involves workshops where trained experts discuss and compile the draft assessment, but it can also be a desk process. Species can be assessed following five criteria (A–E), each operationalizing extinction risk differently. For example, extinction risk might be understood as a steep decline in population (Criterion A) or linked to the species' limited range (Criterion B).[14] Criteria for risk categories are designed to assist assessments even with limited data, to avoid "Data Deficient" classifications, and each species can be assessed based on more than one criterion, which can lead to different assessment estimates. When this is the case, IUCN guidelines encourage assessors to adopt a precautionary approach, utilizing the category with the highest estimated extinction risk.[15] The guidelines also require assessors to document their attitude toward uncertainty and risk in their category attribution.

Step 3: Review Stage The draft assessment is reviewed by a Red List Authority (RLA) or an appointed reviewer. Reviewers must be experts in the redlisting protocol and must not have participated in the assessment phase. Reviewers check for completeness, consistency, and accuracy, providing feedback to the assessors in an iterative process until agreement is reached. This stage involves scrutinizing the assumptions made during the assessment and ensuring that all necessary documentation is provided. The interaction between reviewers and assessors highlights the importance of negotiation and expert judgment in evidential reasoning to obtain a robust assessment, and not mere reliance on data (Bachman et al. 2019).

Step 4: Submission Stage The final report is submitted to the Red List Unit (RLU) in Cambridge, UK. The RLU team, made up of specialists who may not be experienced in the specific taxon under assessment, reviews the evaluations for noticeable errors and ensures consistency with other projects. The submission stage is the final validation stage of the risk assessment, which relies on criteria different from earlier stages. This stage focuses on checking how the A–E criteria have been used, the supporting documentation, consistency, proofreading, and formatting (Bachman et al. 2019). There is a practical tension between the need to base the assessment on abundant data and the accuracy they allow, and the stability and speed at which the assessment must be produced and published. While the IUCN formally encourages uploading all available data about a species to the SIS portal, the large data volume can delay and compromise assessments, and not all data are necessary for the A–E

[14] Plant species, for example, are commonly assessed according to Criterion B (more than 61% of occurrences Le Breton et al. 2019).

[15] See Lam & Majszak 2022 for a philosophical discussion of similar considerations within the expert elicitation protocols in climate science.

criteria to apply. As a result, assessments may require updates by the time they are published, or they might have been produced based on a subset of all the available data.

The three-step Conservation Evidence and the four-step Redlisting protocols underscore that to "bake", so to speak, authoritative knowledge that is potentially (and often practically) policy-relevant, numerous and equally important ingredients are needed. These ingredients include standardized expert judgment, transparently documented rules, negotiations, and methodological rigor. Emphasizing the importance of protocols showcases how the epistemic and ontological assumptions described in Sect. "Evidence-Based Conservation" miss the crucial role fulfilled by other epistemic elements, particularly protocols, in generating reliable and actionable knowledge. Within this view, it is inappropriate to attribute epistemic privilege to data alone based on their alleged representational nature and intrinsic evidential potential. Protocols are put in place especially *because* data do not speak for themselves nor have intrinsic evidential potential. The existence of a step-by-step process, which enforces a system of rules and checkpoints and admits expert elicitation techniques, guarantees the evidential status of knowledge claims. While comprehensive and high-quality data matter, they are not the ultimate determining factors for a claim to be considered evidenced: data must be interpreted and contextualized through structured processes instead.

Sociologists of science often use the phrase "knowledge infrastructure" (Sterner & Elliott 2024) to refer to the material and organizational elements supporting epistemic operations within science and society. The metaphor has already been used to zoom into data practices and the episftemic components involved in the production of knowledge (Leonelli 2020). The knowledge-as-infrastructure metaphor places data journeys within a system of people, communities, and rules, in addition to a mix of socio-political factors and the need for actionable information. Expanding the metaphor, including protocols as outstanding epistemic nodes, helps us zoom out from the epistemic role of data and appreciate that robust, actionable knowledge relies as much on teams of experts and norms as on data.

Conceptual and practical consequences

This analysis has significant conceptual implications for the discourse around evidence in EBC. Zooming in on protocols helps to highlight a disconnect between the data-centric epistemology outlined in Sect. "Evidence-Based Conservation" and actual practices. Data matter to these practices, but their authority and actionability equally depend on institutionalized dynamics, interpretive work, and semirigid standards. In my reading of the EBC discourse, these elements are not described as foundational to evidence, and their epistemic function is usually presented as derivative of the status of data. My critical analysis calls for attention to the triangulation of these epistemic elements in the production of reliable and actionable knowledge. I am not convinced that existing accounts of evidence in EBC accommodate these insights. For example, in one of the most well-articulated attempts to define evidence for EBC, the already-mentioned account by Salafsky et al. argues that evidence is "relevant information used to assess one or more hypotheses related to a question of interest” [p.3]. This definition reduces evidence to the quantifiable support that data and their aggregation warrant for scientific hypotheses or decisions, with limited critical scrutiny and value attributed to the broader picture. By contrast, attending to the various elements in the knowledge infrastructure, their contextual tuning, and their epistemic role exposes the situated and negotiated nature of evidence pro- duction. It enables an understanding of evidence that does not reduce it to a checkbox linking data to justifiable policy.

Whatever form it takes, a proper epistemology for EBC must be both more realistic and more responsible. On the one hand, a more realistic epistemology dethrones data from their epistemic pedestal and openly rejects the claim that data speak for themselves. It recognizes that the reliability and authority of conservation knowledge—such as that produced by Conservation Evidence or the Red List—depend not primarily on the amount or representational quality of data, but on the semi-regimented systems of practices, negotiated evidential thresholds, and the epistemic authority these practices consolidate. These components must be treasured alongside data. This shift opens up space for reflection on the who, how, and why behind standards for what counts as evidence.

On the other hand, and relatedly, a more responsible epistemology acknowledges that different, sometimes competing, knowledge bases, evidential thresholds, and dynamics of knowledge validation are held by diverse communities that contribute to or are affected by conservation—including policymakers, local practitioners, and Indigenous peoples. For example, what information is considered relevant, which methodologies are preferred, and even which axiologies underpin conservation knowledge and practice are not set in stone. It is currently widely recognized that what counts as valid knowledge has long been skewed toward narrowly scientific or quantitative standards, leading to problematic epistemic and social outcomes. A more attentive and caring understanding of evidence—one that centers around the epistemic practices operating in a broader infrastructure—would also support a pluralistic and possibly more inclusive evidence-based approach to conservation.

These conceptual shifts have concrete implications for the current practices within EBC. Here are two. First, the belief that “the bigger the data, the better the evidence”, and the conflation of data with evidence, have so far supported calls to reallocate resources toward data collection—the raw material in knowledge production—and training in data-intensive methods as well as an ethics of data sharing and disclosure, rather than acting on what is seen as incomplete or anecdotal information (Downey et al. 2021; Kareiva et al. 2018; Fox et al. 2017). In this framing, data are treated as an “enduring product of research” and are key to answering multiple questions (Hampton et al. 2013), reinforcing the view that data occupy a privileged and stable place in the knowledge infrastructure. By contrast, drawing attention to other critical junctures in knowledge production opens up alternative paths for resource allocation. One such path could involve investing in qualitative research or building communities of practice—spaces where evidential standards are collectively examined, diverse sources of knowledge are valued, and epistemic and normative assumptions can be openly compared. These efforts may offer a more robust foundation for understanding evidence and decision-making.

Second, a data-centered epistemology underwrites the development of computational tools for evidence synthesis and intervention evaluation that depend on standardized data, often at the expense of attending to the situated realities of conservation within complex sociopolitical contexts. In many EBC synthesis projects, including Conservation Evidence, protocols exclude sources of information that cannot be easily standardized or made legible to computational processing—such as studies without quantified outcomes. This can result in the systematic exclusion of relevant knowledge that could and should be included. Unsurprisingly, the sources most easily sacrificed are the often epistemic and normative resources of communities whose knowledge has long been marginalized in conservation science, including holders of Traditional Ecological Knowledge and Indigenous or local practitioners (e.g. Layden et al. 2025; Pirie et al. 2024). This directly relates to perpetuating epistemic injustices (e.g. Saif et al. 2022). More inclusive approaches to synthesis—those that incorporate grey literature and qualitative knowledge—would make the evidential base more plural, context-sensitive, and responsive to conservation's real-world challenges. In a sense, my analysis contributes to the broader conversation on participatory research and supports the growing movement towards decolonizing conservation science (Corbera, Maestre-Andres, Collins, Mabele, & Brockington, 2024).

In summary: When the infrastructure of knowledge production is brought to light—revealing protocols, evidential standards, and expert judgment as core epistemic tools—the priorities and practices of EBC become open to re-evaluation. This enables reconsideration of how resources should be allocated and what kinds of information and criteria should contribute to the "evidence-based" character of EBC.

Data communities

Before concluding, I would like to draw attention to how the Conservation Evidence and Redlisting protocols tell us something relevant to the discourse around "data communities", a notion that is receiving increasing attention in philosophy, sociology of science, and STS. Data communities are "heterogeneously structured groups of individuals who come together through collectively dealing with shared data" (Bocchi, Cavazzoni, & Castano). Scholars have been using this notion to explain concrete and urgent practices in the life sciences. Recent cases include the study of the technological and material conditions for the formation, development, and changing needs of research collectives and communities of practice in light of datafication and technological innovations (Cavazzoni, under review; Castano, MS; Metcalf, under review; Nyssa et al., MS). I want to call attention to the relationship between protocol implementation and the development and operation of multiple data communities.

Structuring of knowledge production through protocols necessitates designating distinct, usually non-overlapping groups, each of which is tasked with contributing a piece of a bigger puzzle. The implementation of protocols prompts the assembly of individuals, who may be paid or volunteer participants, into units that interact with distinct data subsets and adhere to different rules and norms. Protocols create multiple data communities, each contributing both individually and collectively to the robustness of the final knowledge product.

Protocols also show that it might take more than *one* data community to beget reliable knowledge. In the Conservation Evidence case, three data communities are involved. The project's team produces summaries of token studies, an advisory board produces a synthesis clustering similar tokens into the same type of intervention, and the panel of experts is tasked with labeling each type of intervention according to its degree of effectiveness. In Redlisting, four data communities are involved in each implementation of the protocol, specifically when a species is assigned an extinction label.[16] The pre-assessment coordinators gather data and compile a range map; the assessors use part of the available data to label a species according to its extinction risks; the reviewers provide feedback, while the Red List Unit offers a final check for completeness and consistency, finalizing the assessment for public visibility.[17]

In both examples, each data community is in charge of analyzing different amounts and types of data according to semi-regimented rules, and they can be as temporary as the assignment they need to carry out. What drives the collective is the task of manipulating data and extracting that "piece of knowledge" which needs to be validated and integrated by other communities. To achieve even higher epistemic rigor, data communities cannot overlap. Indeed, when individuals are not allowed to participate in more than one protocol stage, the epistemic oversight these communities exert on each other is strengthened. And amidst each team handling distinct tasks and datasets, their collective operation plays a crucial role in legitimizing the scientific outcome. In addition, the knowledge produced by each community is nested but very diverse due to, among other things, the type and amount of data handled, the tasks attributed to each community, and various non-epistemic factors such as specific considerations around uncertainty and risk attitude. The evidential character of the knowledge produced within these two projects is not a straightforward outcome of data alone but is guaranteed by a stratified system to evaluate and synthesize information from a plurality of different angles.

The data communities generated by implementing protocols operate by abiding by specific evidential standards–sets of rules, more or less regimented and fixed—that guide what counts as good practices around their engagement with data. These evidential standards can either be imposed *top-down* or negotiated *within* or *among* data communities. On the one hand, governing bodies such as the IUCN and the Conservation Evidence leadership constraint the composition and operations of data communities, for example, by setting rules on who can become a member of a community or having power over who is invited to join, which methods and techniques are allowed, which are the minimal statistical thresholds to be met. In the Conservation Evidence project, to be even more specific, the data community responsible for summarizing scientific papers is directed to exclude studies that do not quantify the effects of conservation interventions. In the context of redlisting, the IUCN guidelines impose top-down evidential standards, determining the criteria that must be

[16] At least another data community matters for the redlisting protocol: the team of tax- onomists in charge of classifying species and subspecies, a precondition for each assessment (Witteveen & Bocchi, MS).

[17] Speaking with Red List assessors, it came to my attention that the data collection and the reviewer phase might be appointed to a unique individual, and sometimes the pre-assessment coordinators are also part of the assessment team.

adhered to during a species' assessment. This narrows the focus to particular definitions of extinction risk—although intended to be broad, they may not always apply well to certain taxa.

On the other hand, standards of evidence can be significantly negotiated within a data community, allowing for multiple paths in terms of data selection and interpretation. The flexibility that top-down guidelines allow to the agency of single data communities makes evidential standards "semi-regimented" rather than rigid. In Redlisting, for example, assessors can choose which criteria to utilize in their analysis and thus decide which type of data and theoretical assumptions to prioritize. In the Conservation Evidence protocol, instead, the modified Delphi model used to attribute an effectiveness score leaves room for the experts to amend their initial judgement. However, within-group negotiated standards must pass the scrutiny of other data communities, which might disagree with methodological and theoretical choices. Reviewers and publishers in the Redlisting protocols, for instance, might reject the output of the assessment phase upon arguing that, even if epistemically robust, an assessment must also be actionable and consistent with other similar cases. The panel of experts in the Conservation Evidence project might instead decide to dismiss or incentivize a specific study included in the synopsis due to contextual knowledge.

Conclusion

This paper has critically examined the epistemology of Evidence-Based Conservation (EBC), focusing on the intrinsic evidential value often attributed to data and the broader assumption of data's epistemic privilege. I argued that this view does not withstand philosophical scrutiny: since data must undergo transformative journeys to become evidence, and since evidential standards are shaped by social and institutional factors—data cannot bear evidential value in and of themselves. My analysis has also highlighted how the widespread institution and implementation of scientific protocols is somewhat inconsistent with the privilege attributed to data. Protocols not only underpin solid scientific claims and define what qualifies as valid knowledge to the same extent as data and other epistemic elements, but they also rely on the formation of multiple data communities as additional enablers to the achievement of reliable and actionable knowledge.

Leveraging two prominent examples within EBC—the Conservation Evidence project and the IUCN Red List—I have shown that the production of robust, actionable knowledge occurs as an infrastructure consisting of data, research communities, and semi-flexible evidential standards. Conceptually, my analysis is a call to rethink what qualifies and should qualify as evidence, and which concept of evidence best serves the epistemic and normative purposes of evidence-based policy (Cartwright, 2013). Practically, my analysis raises concerns about the prioritization given to data collection and data-driven methods, as well as the exclusion of certain sources of knowledge in data synthesis.

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