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RESEARCH ARTICLE

Twenty Years of Evidence–Based Conservation: Progress, Promise, and Future Directions

Evidence-based practice is spreading but still limited in conservation and environmental management

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Abstract

1. Over two decades after the first calls for evidence-based conservation (EBC), the accessibility of scientific evidence has improved through syntheses and databases, and initiatives such as the Conservation Evidence project's 'Evidence Champions' have promoted more routine evidence use. However, the extent to which evidence-based practice (EBP) has been adopted across conservation and environmental management remains unclear.
2. We quantified proxies for the prevalence of EBP using keyword-based and machine learning approaches applied to ~162,000 job adverts (2002–2025) from three job boards (Conservation Careers, Environment Job and Countryside Jobs Service) covering UK and international posts. In parallel, we analysed trends in EBP-related terms in the grey and scientific literature over the same period.
3. Mentions of EBP increased at an accelerating rate: 4.2% per year on average in the grey literature, 8.8% per year in the scientific literature and 13–16% per year in job adverts. The proportion of organisations mentioning EBP in job adverts also increased by 13% per year on average. Despite this growth, current prevalence remains modest, appearing in only 2%–6% of job adverts from 5% to 8% of organisations, with higher prevalence in the public sector than in the charity/not-for-profit and private sectors.
4. Diffusion modelling indicated EBP probably spreads via a 'slow–fast–slow' dynamic consistent with diffusion of innovations theory (i.e. a sigmoidal model). This model estimated that approximately 90% of organisations may never adopt EBP, although current trends point to an accelerating early-adopter phase, making forecasts of saturation and non-adopters uncertain. Further research using longitudinal and social science methods is needed to assess actual levels of EBP implementation and the key factors influencing this.
5. *Solution*: Wider uptake of EBP and EBC could be facilitated by more intensive engagement at different stages of adoption, helping to embed evidence step-by-step within existing workflows. Achieving this requires clear guidance on what meaningful EBP looks like in practice, tailored support for implementation and awareness of potential 'evidence-washing' (claims of being evidence-based

without meaningful implementation). Incentives, recognition and accreditation could help reward genuine adopters and create the enabling conditions for a cultural shift towards routine evidence use that will underpin more effective conservation and environmental action.

KEYWORDS
adoption, conservation evidence, diffusion of innovations, evidence, evidence-based conservation, evidence-based practice, evidence-informed conservation, grey literature, machine learning

1 | INTRODUCTION

Evidence-based practice (hereafter EBP) originated in medicine in the 1970s and has been credited with improving outcomes in medical practice (Connor et al., 2023; Dawes et al., 2005). Defined as the systematic use of the best available evidence to inform decisions and action (Guyatt, 1992; Sackett et al., 1996), the concept of EBP has since been introduced to many other fields, including biodiversity conservation and environmental management, with the expectation that it would improve outcomes there too (Cooke et al., 2023; Cvitanovic et al., 2016; Pullin & Knight, 2009; Sutherland et al., 2004).

For example, approximately two decades ago, 'Evidence-based Conservation' (EBC; Pullin & Knight, 2003; Sutherland, 2000, 2003; Sutherland et al., 2004) was promoted to overcome the perceived over-reliance of conservation practice and policy on using personal experience and anecdotes to inform decisions (Pullin et al., 2004). The concept has since evolved, including suggestions to rename it 'evidence-informed conservation' (Adams & Sandbrook, 2013) as well as debates over what counts as evidence and how various forms of evidence can support decisions (Bennett, 2016; Christie et al., 2022, 2023; Salafsky et al., 2019). Recent discourse suggests that the principles of EBC also encompass transparent documentation of how decisions are made and the evidence underpinning them, drawing together both local knowledge and experience alongside global research to tailor evidence to inform decisions (Christie et al., 2022, 2023; Malmer et al., 2020; Rowland et al., 2023; Salafsky et al., 2022; Sutherland, 2022). A central tenet of EBC is that those working in conservation contribute back to the evidence base where possible by documenting and sharing their findings to drive improvements in conservation efforts (Caruana et al., 2024; Downey et al., 2022; Ockendon et al., 2021; Sutherland et al., 2020).

Despite two decades of discussion, it remains unclear whether those working in conservation and environmental management, particularly practitioners, are becoming more aware of and adopting EBP. Persistent barriers continue to hinder its uptake (Rose et al., 2018; Walsh et al., 2019), such as limited time, expertise or access to relevant evidence to apply it to inform practice and policy. Some have blamed poor uptake on 'evidence complacency', where evidence is perceived to be ignored and not consulted, potentially resulting in negative impacts on practice and policy (Sutherland & Wordley, 2017). One reported example of this are bat gantries, on which millions of pounds have been spent to mitigate bat mortality on UK roads with little evidence of effectiveness (Berthinussen & Altringham, 2012; Sutherland & Wordley, 2017). Of course, problems with the uptake of EBP do not solely rest with the users of evidence, but across the science–policy–practice interface, including challenges on the supply side of evidence, such as how relevant evidence is made accessible and communicated to end-users (O'Connell & White, 2017). However, we still lack baseline estimates of levels of awareness and uptake of EBP in conservation and environmental management.

Diffusion of innovations theory (Rogers, 2003) could be a useful theoretical framework to help understand the adoption of EBP, which has been widely applied across different fields, including medicine, business, agriculture, economics and education (Wejnert, 2002). This theory posits that new ideas or practices diffuse through a population as adoption by 'innovators' increases the likelihood of adoption by others (Rogers, 2003, Strang, 1991). Adoption is suggested to spread through five adopter categories: 'innovators' (~2.5% of a population of adopters), followed by 'early adopters' (13.5%), the 'early majority' (34%), the 'late majority' (34%) and finally 'laggards' (16%) (Rogers, 2003; Figure 1).

Previous studies have applied this theory to conservation, showing that the adoption of area-based conservation initiatives follows a 'slow–fast–slow' (sigmoidal) trajectory (Figure 1; Mascia & Mills, 2018; Mills et al., 2019). Applying this approach to the adoption of EBP could help identify how it is spreading, how rapidly adoption is occurring, and how widespread it is currently and may become in future. This will help to clarify how much progress has been made over the past two decades and identify opportunities to accelerate uptake within the conservation and environmental management community.

We examined proxy indicators of EBP awareness and adoption in conservation and environmental management through three data types: two repositories of grey literature (Overton and Applied Ecology Resources), two bibliographic databases of scientific literature (Scopus and Web of Science) and three job board databases (Conservation Careers, Countryside Jobs Service and Environment Job). We analysed the occurrence of EBP-related keywords to estimate levels of awareness over time, complemented by a machine learning classifier to provide a more liberal estimate of mentions of

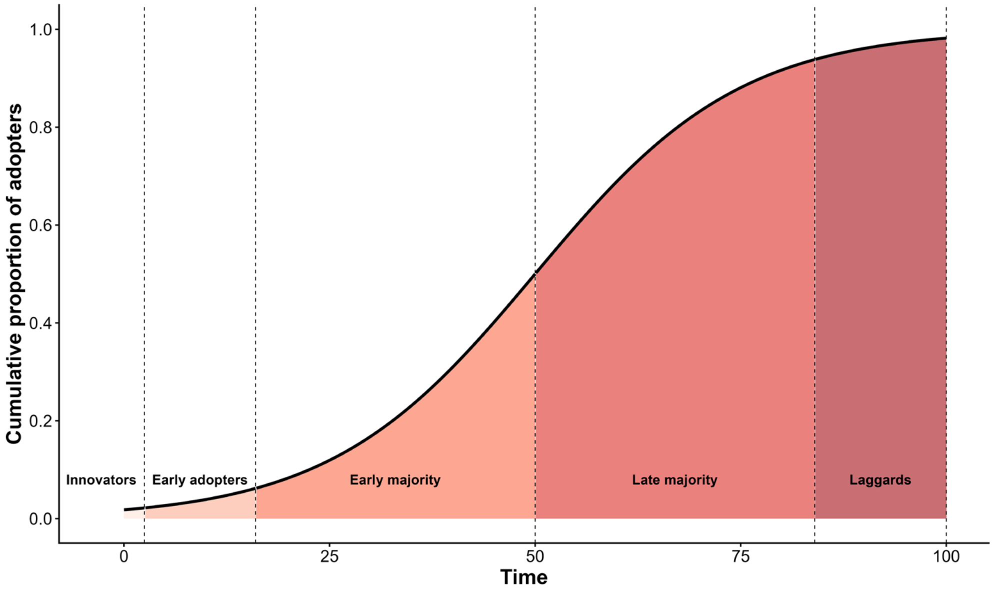

FIGURE 1 Illustrative diagram of the cumulative adoption of an innovation over time, showing the characteristic S-shaped diffusion curve and the five adopter categories described in diffusion of innovations theory (innovators, early adopters, early majority, late majority and laggards; Rogers, 2003).

EBP in job adverts. Together, these approaches offer likely lower and upper bounds of EBP awareness and potential adoption. We also explore sectoral differences and model the diffusion dynamics in the potential spread of EBP among conservation and environmental management organisations, drawing on diffusion of innovations theory and methods from Mills et al. (2019).

2 | MATERIALS AND METHODS

2.1 | Grey and scientific literature data

To gather proxy data on the awareness and adoption of EBP in the conservation and environmental management literature, we searched two grey literature databases: 1. Overton (https://www.overton.io/), a general, but expansive, international collection of documents from policy and practice organisations; and 2. Applied Ecology Resources (https://www.britishecologicalsociety.org/applied-ecology-resources/), a more discipline-specific grey literature repository of mainly practitioner-relevant documents on conservation and ecological management. We also searched two scientific literature databases for more academic research on EBP: SCOPUS and Web of Science (Core Collection).

We conducted two searches per database, one to estimate the total number of conservation and environmental management articles, and another to estimate how many of these mentioned EBP-related keywords (see search strings—Table S1). We recorded all results from 2002 to 2025, inclusive, and by publication year separately. We searched each database, with Imperial College London subscription access where required, and using the 'Full Text' field (Overton), 'All fields' (Scopus and Web of Science Core Collection—all editions) or search bar function (Applied Ecology Resources, specifying 'YR=' in the search string to set the years for the search). We report the total number of articles found from these searches in the Results (Section 3.1).

2.2 | Job board databases

2.2.1 | Job-advert preprocessing

We also obtained proxy data for the awareness and adoption of EBP in conservation and environmental management from three job-advert databases: Conservation Careers (86,102 adverts, 2013–2024), Countryside Jobs Service (14,532 adverts, 2017–2024) and Environment Job (66,707 adverts, 2002–2025). We selected these because, to our knowledge and at the time of writing, they were the most comprehensive databases available for conservation and environmental jobs that would allow us to freely access their data.

To ensure the quality and appropriateness of these datasets for our research aims, we first removed any job adverts labelled as voluntary, unpaid or internships. We cleaned job-advert descriptions for each dataset by removing html text, converting to lowercase, expanding common abbreviations and removing punctuation. We detected duplicates using both semantic comparisons (TF-IDF vectorisation and Cosine similarity) and sequence matching (character-level similarity) to generate composite similarity scores (60% TF-IDF and 40% character similarity), removing duplicates above a threshold of 0.92 after inspecting borderline cases (at thresholds of 0.85 to 0.95 at 0.01 intervals). We also screened job descriptions for poor-quality or very short text, removing adverts with fewer than 350 characters after inspecting a random sample of 20 adverts across thresholds from 200 to 500 characters in 50-character intervals. This left us with 81,688 adverts for Conservation Careers, 14,279 adverts for Countryside Jobs Service, and 65,929 adverts for Environment Job.

To determine the number of organisations in the datasets, we pooled and deduplicated organisation names using an automated process as there were initially 19,990 unique names. Organisation names were often not recorded for the years 2002–2005 so these were removed from this analysis. First, we cleaned names by converting all text to lowercase, removing punctuation, non-printable characters and common business suffixes (e.g. 'ltd', 'inc'). We standardised spellings by converting to US English terms (e.g. 'organisation' to 'organization') and corrected a predefined list of known typographical errors based on manually inspecting a random 10% of names. We also converted simple plural forms to singular, and extraneous whitespace was removed to create a standardised version of each name. We vectorised the cleaned names by first tokenising each one into character n-grams (two to four characters) to help detect minor spelling variations and typos. From these n-grams, a document-term matrix (DTM) was constructed and we applied the Term Frequency–Inverse Document Frequency (TF-IDF) algorithm, giving higher scores to n-grams that are frequent within a specific name but rare across the entire set of names. We produced a distance matrix using the cosine similarity between the TF-IDF vectors of all pairs of names (distance = 1 − similarity) and performed hierarchical agglomerative clustering to group names based on the maximum distance between members of potential clusters. We used a distance threshold of 0.7 to partition distinct clusters (after manually inspecting the resulting dendrogram) and renamed all organisational names within a single cluster to a 'canonical name', which was used for the rest of the analyses ($n = 12{,}559$ canonical names).

2.2.2 | Job-advert classification

To detect the prevalence of EBP mentions in job descriptions for these large datasets, we used two automated approaches: (1) keyword searches to give a conservative estimate and probable lower bound; (2) machine learning classification focusing on maximising recall to give a liberal estimate and probable upper bound. For the first approach, we used the same EBP-related keywords as those in the search strings for the grey and scientific literature (Table S1) and labelled each job advert with a binary label (1 = EBP keywords present, 0 = EBP keywords absent).

For the second approach, to train a machine learning classifier we created a manually labelled dataset of job adverts. We first used random stratified sampling, accounting for each dataset and publication year (using four bins between 2002 and 2025) with the aim of generating approximately 150 samples per stratum. This generated an initial sample to label of 1249 adverts.

To label an advert as mentioning EBP, our criteria were that they could not simply state that the organisation or role holder would follow best practice, but had to also mention either reviewing documentation or literature to collate and identify best practice. Sharing best practice or following best practice, as well as collating evidence on project outcomes for funder reports, were also deemed insufficient. Similarly, only mentioning adaptive management would not be classified as EBP—although it is related to EBP and EBC, it typically emphasises a planning and learning cycle within a particular context, and does not specifically require learning and sharing across other contexts (e.g. consulting and adding to the wider literature; Gillson et al., 2019). We also looked for key terms, such as 'evidence-based' or 'evidence-informed' and if these were mentioned appropriately we labelled as mentioning EBP (i.e. to deliberately provide a liberal estimate and probable upper bound). We labelled positively if there were mentions of reviewing literature or collecting evidence to support decisions, such as conducting research to find best practice according to definitions of EBP and EBC. Our manual labelling resulted in 127 positive examples (mentioning EBP) and 1122 negative examples (not mentioning EBP).

As unbalanced datasets can lead to poor classification, we down-sampled our dataset by removing excess negative examples, whilst trying to balance the number of samples as evenly as possible between publication year bins and databases. We achieved a more balanced 2.5:1 negative to positive ratio (compared with 10:1 previously), bearing in mind the need to retain a sufficiently large sample size for training and validating our machine learning classifier. Our final training set for classification gave us a total of 445 adverts, composed of 318 negative examples and 127 positive examples.

We applied a feature engineering approach by generating count and binary presence features for each keyword category (direct evidence terms, research methods and conservation-specific terms—Table S2), which were expanded with plural forms. We supplemented these features with Term Frequency–Inverse Document Frequency (TF-IDF) vectorisation (5000 features maximum, 1–3 grams) for richer feature representation to ensure we could find as many job adverts as possible that mentioned EBP.

The classifier we used was a Random Forest with Synthetic Minority Oversampling Technique (SMOTE) to account for the class imbalances in our dataset. We used the following hyperparameters: 100 estimators (trees) to provide stable predictions, a max tree depth of 10, at least five samples to split nodes, and 'leaves' with at least two samples to prevent overfitting. Before running the classifier, we also normalised features as the keyword counts and TF-IDF values occur on different scales. We trained and tested our classifier by splitting the dataset, stratified by positive and negative classes, into 80% training data ($n = 101$ positives, 254 negatives) and 20% validation test data ($n = 26$ positives, 64 negatives). We evaluated performance thresholds from 0 to 1, selecting 0.5 based on the model's performance on the validation test data, which maximised recall and precision (results for other thresholds can be found in Table S3). At a threshold of 0.5, the classifier achieved a positive F1 score of 0.96 (0.99 for negatives), positive recall of 0.92 (1.00 for negatives) and positive precision of 1.00 (0.97 for negatives; Table S3). This

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suggested our classifier was suitable for generating predictions with relatively high recall on whether a job advert was likely to mention EBP, satisfying our requirement for a probable upper bound estimate.

For the Conservation Careers dataset, data were also available on the job sector for each advert from the UK, enabling us to analyse the prevalence of EBP mentions by job sector. We modified the job sector classifications for this dataset and added classifications where organisations lacked data using three groupings: (1) Charity/not-for-profit: organisations listed as a charity or operating as a not-for-profit; (2) Public: government-funded/operated agencies, departments or bodies, including councils and public sector partnerships; and (3) Private: commercial companies, consultancies and for-profit businesses.

2.3 | Analysis

All analyses were carried out using R statistical software version 4.4.0 (R Core Team, 2024), except where stated otherwise.

2.3.1 | Literature analyses

To determine whether there were changes over time in the probability that publications mentioned EBP terms, we fitted a binomial mixed-effects logistic regression model with a logit link function. The response variable was the number of articles mentioning EBP terms out of the total number of articles in conservation and environmental management for each database-year combination (i.e. a binomial model with varying denominators). The fixed effects were rescaled year (in decades) and literature type (scientific literature: Web of Science and Scopus databases; grey literature: Overton and Applied Ecology Resources databases), including their interaction (rescaled year × literature type) to allow temporal trends to differ between grey and scientific literature. Database was included as a random intercept (the four listed above) to account for baseline differences among literature sources whilst estimating overall literature type-level trends.

We selected the interaction model because an analysis of deviance (Type III Wald chi-square tests) indicated strong evidence for different temporal trends between grey and scientific literature (rescaled year × literature type: $\chi^2 = 2578.8$, df = 1, $p < 0.0001$), and diagnostics showed that this model specification captured the main data structure. Model assumptions were evaluated using the Dharma package (Hartig, 2024), which indicated no evidence of overdispersion or zero-inflation and no problematic outliers or residual patterns. From the fitted model, we obtained estimated yearly changes in the proportion of articles mentioning EBP terms for each literature type using marginal trends (using the emmeans package; Lenth, 2025), and we derived 95% confidence intervals and tests for differences between grey and scientific literature from these marginal estimates.

2.3.2 | Job-advert analyses

To assess whether there was a statistically significant change in the probability that job adverts mentioned EBP over time, we fitted a separate binomial logistic regression model with a logit link. The response variable was whether an individual advert was classified as mentioning EBP (yes/no), and the explanatory variables were year and estimation method (machine learning classifier versus keyword terms). We compared a main-effects model (year + method) with an interaction model (year × method) using Akaike information criterion (AIC) and a likelihood-ratio test. We selected the interaction model as this had a lower AIC by more than 2 units (ΔAIC = 19.6) and an analysis of deviance test indicated a significant year × method (deviance = 21.6; df = 1; $p < 0.0001$), showing that temporal trends differed between the two estimation methods. Model assumptions were evaluated as before using the Dharma package (Hartig, 2024) and we found no evidence of overdispersion, zero-inflation, problematic outliers or residual patterns. From the final model we derived method-specific yearly changes in the odds and percentage of adverts mentioning EBP terms, together with 95% confidence intervals and tests for differences between the keyword and classifier approaches from marginal estimates (Lenth, 2025).

We repeated this process with an equivalent model to investigate changes in the number of organisations mentioning EBP over time in their job adverts. We selected the main-effects model in this case as it was the most parsimonious model, given there was a less than 2 unit difference in AIC (ΔAIC = 0.21) and an analysis of deviance test found no significant year × method interaction (deviance = 2.2, df = 1, $p = 0.1370$).

To determine whether the observed number of jobs that mentioned EBP or not varied by job sector (public, private or charity/not-for-profit), we used the Conservation Careers dataset (the only one containing data on the sector of job adverts) and a chi-squared test. We repeated this test for the keyword and machine learning classifier approaches and conducted post hoc pairwise comparison of proportions tests (using a Bonferroni correction to calculate adjusted p-values for multiple testing) to check for significant differences between sectors.

To understand levels of adoption in line with diffusion of innovations theory, we used methods from Mills et al. (2019) to determine which type of diffusion model best fitted our job-advert data. We first aggregated by organisation, deduplicating organisation names, and counted the cumulative number of unique organisations in each year that mentioned EBP in a job advert, as well as the total cumulative number of unique organisations. We used the total cumulative number of organisations up to 2025 as the best estimate of the maximum potential number of organisations that could adopt EBP. Following methods and code from Mills et al. (2019) implemented in MATLAB (The MathWorks Inc, 2025), we fitted and compared three candidate models to explain the adoption of EBP: a constant (linear) curve, an asymptotic (R-shaped) curve and a diffusion (sigmoidal or S-shaped) curve.

These models estimated the number of receptive organisations that would eventually adopt EBP ('effective maximum uptake'), the number that would never adopt (so-called 'resistant' organisations—although note this terminology does not mean organisations necessarily resist adoption in a deliberate way), and the percentage of receptive organisations that had adopted EBP over time to the present. Uncertainty estimates around each curve were generated with block bootstrapping, to account for the temporal dependency of the data, with blocks of 5 years (Mills et al., 2019). We determined the model with the best fit to the data using R^2 values and AIC—see the Results (Section 3.2).

As we included an incomplete year of job-advert data for 2025, we tested whether removing this year of data affected our results. Our sensitivity analysis (Table S5) found that results for each of our main analyses changed negligibly and had no meaningful impact on our major findings.

3 | RESULTS

3.1 | Grey and scientific literature

We found the following numbers of articles published between 2002 and 2025 mentioned EBP-related keywords out of all articles mentioning conservation and environmental management keywords: Overton = 76,460 out of 2,315,653 (3%); Applied Ecology Resources = 454 out of 2973 (15%); Scopus = 178,660 out of 1,349,608 (13%); and Web of Science = 3673 out of 367,212 (1%).

There was a notable increase over time in the percentage of articles mentioning EBP keywords in the conservation and environmental management literature (year effect: $\chi^2 = 8161.6$, $df = 1$, $p < 0.0001$; Figure 2). The change over time in the percentage of articles with EBP terms was significantly different between grey and scientific literature databases (year × type interaction: $\chi^2 = 2578.8$, $df = 1$, $p < 0.0001$).

In the grey literature (Overton and Applied Ecology Resources), the percentage of articles with EBP terms rose by 4.2% per year (95% CI 4.1–4.3, $p < 0.0001$), whereas in the scientific literature (Web of Science and Scopus), this rose by 8.8% per year (95% CI 8.6–9.0, $p < 0.0001$). The yearly increase in the scientific literature was therefore substantially greater than that in the grey literature (difference in slopes: $z = 50.8$, $p < 0.0001$). However, whilst the relative growth was faster in the scientific literature, the absolute change in the percentage of articles with EBP terms was substantially greater for the grey literature databases (from 2002 to 2025: Overton = 7.3% to 19.8%; Applied Ecology Resources = 0% to 10.9%) than for Scopus or Web of Science (0.7% to 5.3%, 0.5% to 1.8%, respectively).

The terms associated with EBP varied considerably in their frequency as a percentage of the total number of articles mentioning any EBP term (Table S4). In the scientific literature, the term 'evidence-based' was highly common (54% of articles mentioning EBP terms; Table S4) compared with alternatives, such as 'evidence-informed' (3.8%) and 'evidence-led' (0.1%). The terms 'research-based' (11.0%) and 'science-based' (19.1%) were the next most frequently mentioned terms (aside from 'scientific evidence' at 14.3%). The same was true for the grey literature, except the term 'evidence-based'

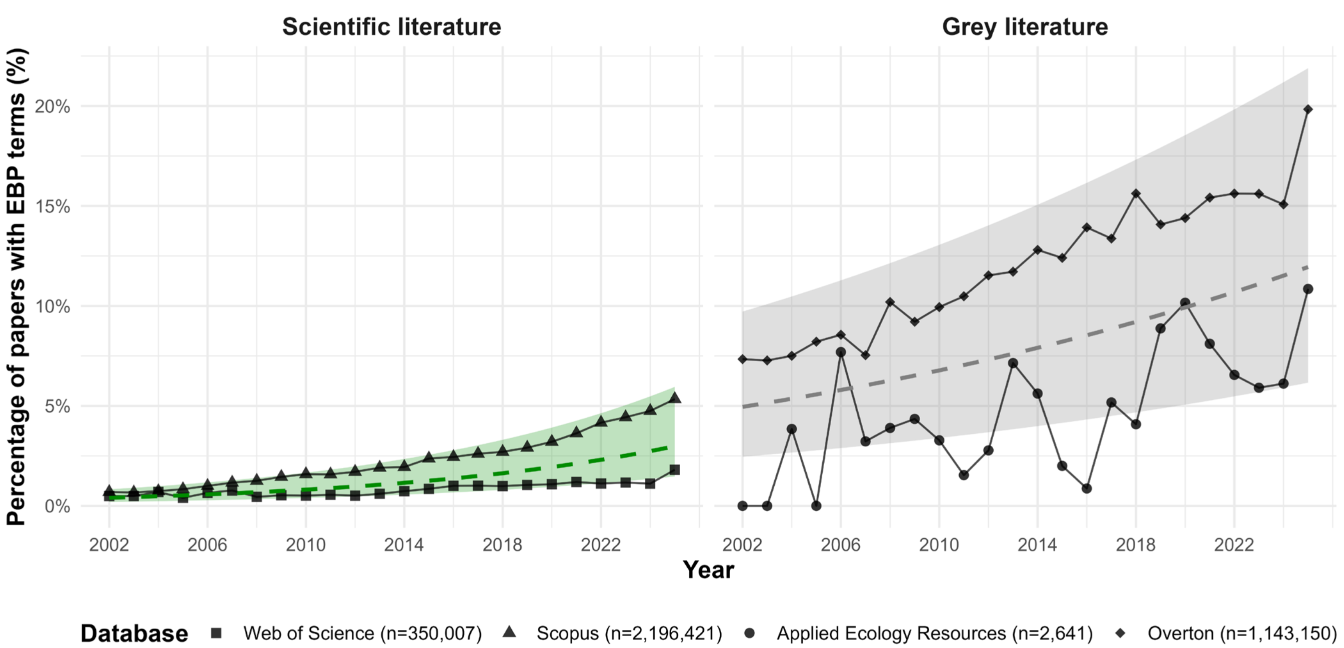

FIGURE 2 Percentage of articles mentioning evidence-based practice keyword terms in grey and scientific literature databases from 2002 to 2025 (out of all articles mentioning conservation and environmental management keywords). Observed data points for each database are shown with solid lines and symbols, whilst dashed lines and shaded areas represent estimated marginal means and 95% confidence intervals from a binomial mixed-effects model.

was even more commonly used (74.7%; Table S4) relative to other terms, whilst 'science-based' (16.7%) and 'research-based' (6.2%) were still the next most common terms (albeit less so in percentage terms). The term 'evidence-based conservation' was more frequently used relative to 'evidence-based practice' in the scientific literature (6.1% vs. 2.1%), but in the grey literature, the opposite pattern was observed (3.4% vs. 7.7%; Table S4).

3.2 | Job board adverts

We found that there was an increase over time in the percentage of jobs mentioning EBP across all databases for both the machine learning classifier method (average 2002–2006 = 0.6% to average 2021–2025 = 6.2%; Figure 3) and the keyword method (average 2002–2006 = 0.6% to average 2021–2025 = 2.3%). We found that the percentage of jobs mentioning EBP per year increased significantly over time and that temporal trends differed significantly between the classifier and keyword methods (Figure 3; Type III: $\chi^2 = 22.1$, $df = 1$, $p < 0.0001$). The classifier method estimated a yearly percentage increase in job adverts mentioning EBP of 16.3% per year on average (95% CI: 15.4%–17.2%), whilst the keyword method estimated this at 12.5% per year (95% CI: 11.3–13.8%). The interaction model (year × estimation method) had a McFadden's pseudo-R^2 value of 0.05, indicating a small proportion of the variance in mentions of EBP was explained.

Most job adverts were related to the UK (73.2% of jobs), significantly fewer of which mentioned EBP (2.9%) versus the rest of the world (6.5%) based on the classifier method ($\chi^2 = 1045.0$, $df = 1$, $p < 0.0001$)—although for the keyword term method, the difference was negligible and marginally statistically significant (1.5 vs. 1.7% for classifier and keyword methods, respectively; $\chi^2 = 4.9$, $df = 1$, $p = 0.0270$).

We found that the percentage of organisations with job adverts mentioning EBP each year has increased at an accelerating rate over time since 2006 for both the classifier and keyword methods (Figure 4; Type III: $\chi^2 = 541.3$, $df = 1$, $p < 0.0001$). We found no significant year × method interaction (*deviance* = 2.2, $df = 1$, $p = 0.1370$ —we used a main-effects model for this analysis, see the Methods, Section 2.3), and so the trends observed did not differ substantially between estimation methods. For the classifier method, the percentage of organisations mentioning EBP rose from an average of 1.0% in 2006–2008 to 7.8% in 2021–2025, whilst for the keyword method, the increase was from an average of 0.5% in 2006–2008 to an average of 4.9% in 2021–2025. The yearly percentage increase in organisations mentioning EBP was 12.5% per year on average (95% CI: 11.4%–13.6%). The non-interaction model (year + estimation method) had a McFadden's pseudo-R^2 value of 0.04 and therefore

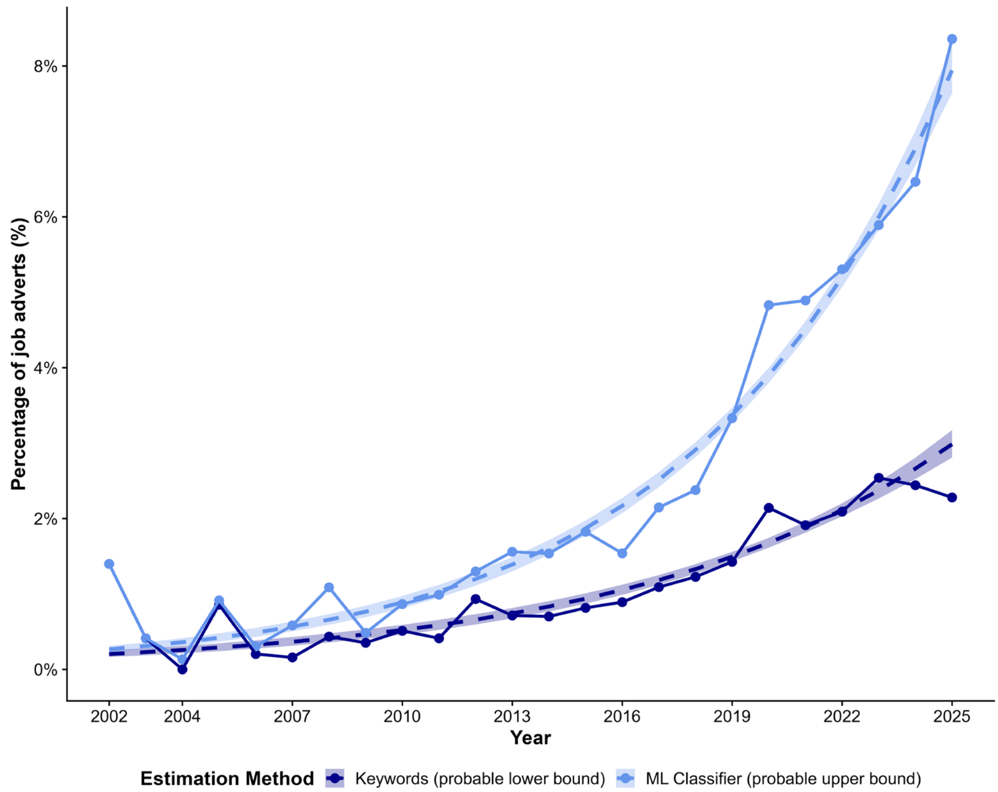

FIGURE 3 Percentage of job adverts classed as mentioning evidence-based practice by keyword or machine learning (ML) classifier methods from three job board databases: Conservation Careers, Countryside Jobs Service and Environment Job, from 2002 to 2025. Observed data points joined by solid lines are plotted alongside logistic regression model conditional predictions and associated 95% confidence intervals represented by dashed lines and bands. Data for 2025 were incomplete so may not be representative of whole year, but this did not affect our findings (see the Methods, Section 2.3, Table S5).

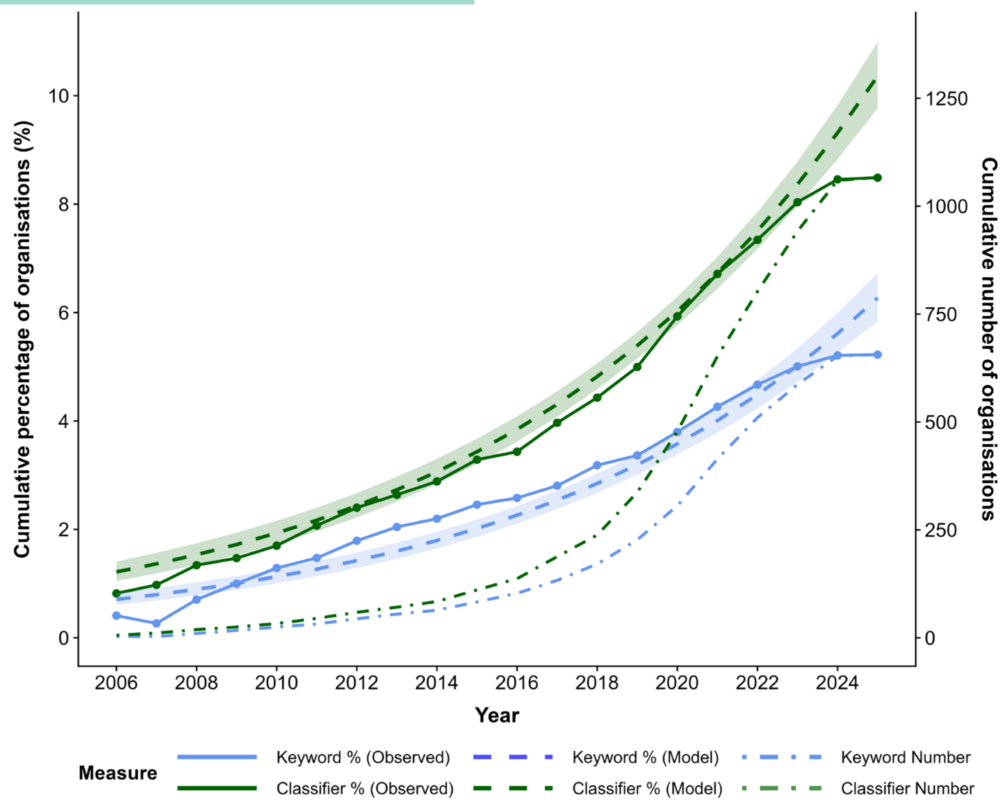

FIGURE 4 Cumulative percentage of organisations mentioning evidence-based practice in job adverts (left *y*-axis—solid points and lines) alongside the cumulative number of organisations (right *y*-axis—dotted lines) from 2006 to 2025. Observed data points are joined by solid lines and plotted alongside logistic regression model conditional predictions and associated 95% confidence intervals (dashed lines and bands). Cumulative percentages are calculated by dividing the cumulative number of organisations mentioning evidence-based practice by the cumulative number of all organisations up to each year. Organisation names were often unavailable for the years 2002–2005 and were removed from the analysis. Data for 2025 were incomplete so may not be representative of the whole year, but this did not affect our findings (see the Methods, Section 2.3, Table S5).

explained a small proportion of the variance in mentions of EBP by organisation.

We found that a diffusion (sigmoidal) model fitted the data the best (lowest AIC and highest adjusted R^2 compared with linear and asymptotic models; Figure 5), representing slow–fast–slow dynamics. The diffusion model predicted that the average percentage uptake of the potential organisations that may adopt EBP in the future (i.e. as a percentage of effective maximum uptake) was 82%–84% in 2025 (keywords and classifier method averages, respectively). The maximum number of organisations that would eventually adopt EBP was estimated at 845 organisations (keyword) and 1320 organisations (classifier). With a total of 12,559 organisations, the number of resistant organisations who are predicted to never adopt EBP in the future was estimated at 11,714 (keyword) and 11,239 (classifier), or 93% (keyword) and 89% (classifier) of the total number of organisations.

Using the Conservation Careers dataset (restricted to the UK) and classifier method, we found that UK jobs from the public sector were more likely to mention EBP (5.4%) than the charity/not-for-profit sector (4.4%), and both in turn were more likely than the private sector (1.9%) (overall: $\chi^2 = 95.4$, $df = 2$, $p < 0.001$; post hoc pairwise comparisons of proportions: charity-private $p = 0.015$; charity-public $p < 0.0001$; private-public $p < 0.0001$). Similar differences were found for the keyword method, with a more pronounced difference between the public sector versus other sectors: public (4.3%), charity/not-for-profit (1.7%) and private (1.1%) (overall; $\chi^2 = 175.5$, $df = 2$, $p < 0.0001$; post hoc pairwise comparisons of proportions: charity-private $p < 0.0001$; charity-public $p = 0.0036$; private-public $p < 0.0001$).

4 | DISCUSSION

4.1 | Evidence of accelerating but limited uptake of EBP

Our analyses indicate that mentions of EBP have increased, and in most cases accelerated, since the early 2000s across the scientific literature, grey literature, and, to a lesser extent, conservation-related job adverts. Even using methods designed to provide conservative and liberal estimates, the prevalence of EBP mentions in recent job adverts remains low (2%–6% of adverts from 5% to 8% of organisations). Mentions in the grey literature were more frequent (11%–20% in 2025) than in the scientific literature (2%–5%). These

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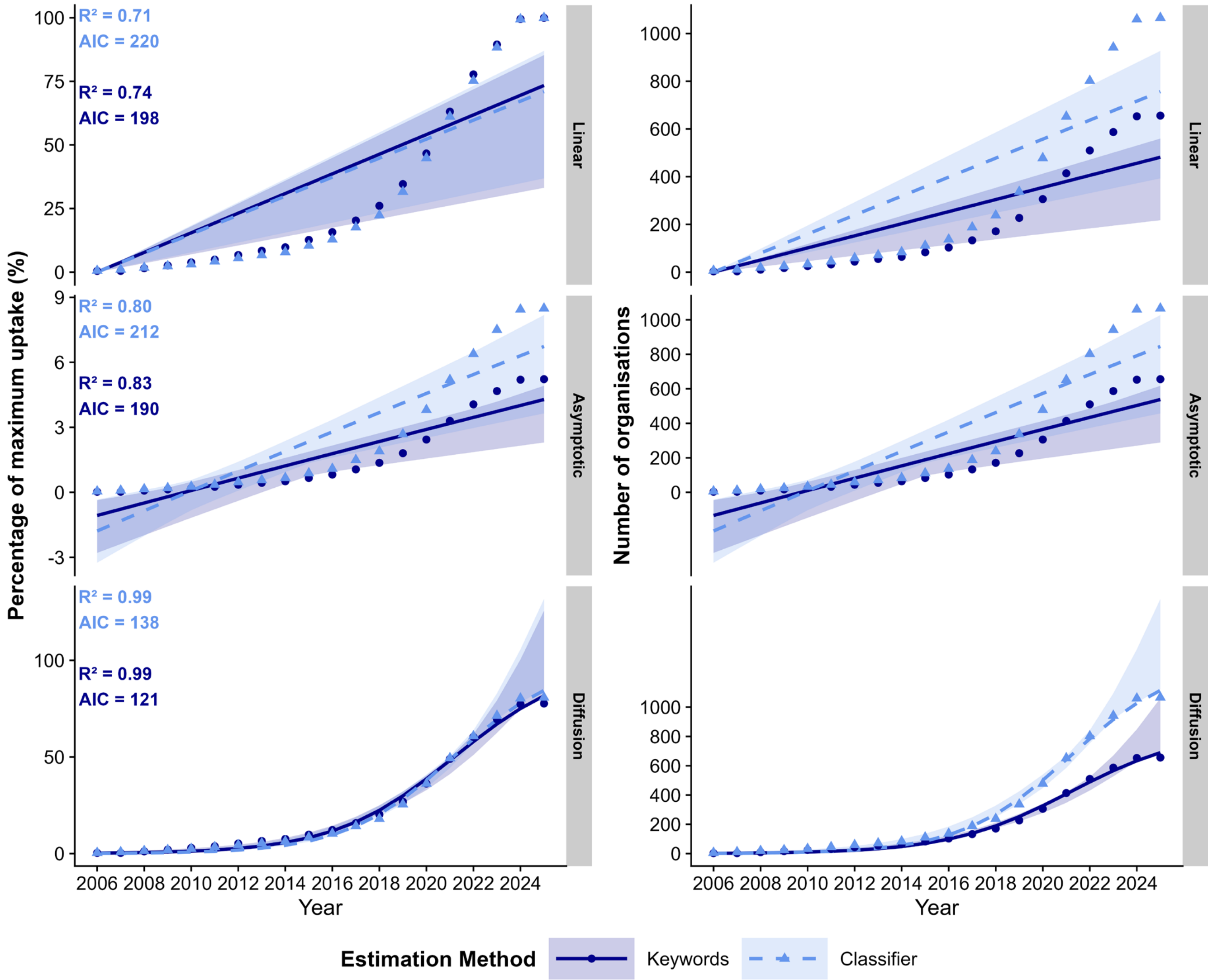

FIGURE 5 Predictions from different candidate adoption models on the percentage of organisations (out of the predicted effective maximum number of receptive organisations; left column) and the cumulative number of organisations (right column) adopting evidence-based practice based on mentions in job adverts from 2006 to 2025. Predictions and associated 95% Confidence Intervals (lines and bands—dark blue for keyword method; light blue for classifier) are presented from three candidate models: linear, asymptotic and diffusion (sigmoidal). Observed percentages and number of organisations are presented as points (circle = keyword method; triangle = classifier). Statistics reflecting model fit (R^2 and Akaike information criterion) for the models using percentage uptake are presented in the top left corner of the plots. Organisation names were often unavailable for the years 2002–2005 and were removed from the analysis. Data for 2025 were incomplete so may not be representative of whole year, but this did not affect our findings (see the Methods, Section 2.3, Table S5).

patterns suggest that EBP diffusion in conservation, and environmental management is still in an 'early-adopter' phase, consistent with the rising segment of the 'S-shaped' adoption curve proposed by diffusion of innovations theory (Rogers, 2003).

Interpreting these results requires caution because our metrics capture awareness and signalling of EBP rather than verified implementation. In the diffusion of innovations literature, adoption can range from a decision to adopt to the full implementation of an innovation (Mills et al., 2019; Wolfe, 1994). The indicators we used are best viewed as evidence of decisions to adopt—early expressions of intent rather than confirmed behavioural change.

Among our proxies, publications in the scientific literature are likely the most indirect indicator, reflecting discussion within academic and research circles. Mentions in the grey literature, such as organisational strategies or reports, indicate that a modest proportion of practitioner organisations are recognising EBP principles and using consistent terminology. Job advertisements probably provide the most direct organisational-level signal, showing when EBP becomes an expected competency or part of role or organisational descriptions. Whilst these data cannot confirm implementation, they do suggest that the enabling conditions for EBP—such as organisational awareness, perceived value and infrastructure for evidence use—are beginning to become established in a small minority of organisations (O'Connell et al., 2024).

Assuming job adverts reflect some genuine adoption decisions, our findings align with a sigmoidal diffusion pattern where uptake proceeds slowly among innovators, accelerates through early adopters, and later plateaus (Rogers, 2003; Figure 1). Similar dynamics ('slow–fast–slow' growth) have been observed in other conservation innovations (area-based conservation initiatives; Mills et al., 2019; Romero-de-Diego et al., 2021), typically spreading via peer-to-peer exchange rather than top-down mandates—which is theorised to follow an asymptotic 'R-shaped' curve (Clark et al., 2022). However, in Rogers's (2003) theory, adopter categories were developed primarily for the decisions of individual adopters, and so we must be cautious in using this to explain adoption by organisations that may be governed more by collective and institutional dynamics (Damanpour & Schneider, 2006).

Indeed, estimating the eventual ceiling of adoption ('effective maximum uptake') remains difficult in this early, acceleration stage (Clark et al., 2022). Without future research to clarify the shape and steepness of the adoption curve, we cannot yet confidently identify the proportion of organisations that are unlikely to ever adopt. In diffusion terms, these organisations are 'laggards' or 'resistant' non-adopters, but in practice, this does not necessarily reflect active resistance but persistent barriers. These may include limited resources, time constraints, uncertainty about EBP's return-on-investment (Christie et al., 2025), lack of know-how, 'evidence complacency' (Sutherland & Wordley, 2017) or misplaced confidence that existing practices are already evidence-based (Christie et al., 2025; Rose et al., 2018; Walsh et al., 2019). Such barriers align with broader findings that resource limitations, perceived risk and organisational inertia often dampen innovation diffusion (Greenhalgh et al., 2004; MacVaugh & Schiavone, 2010).

Nevertheless, with the data available, our diffusion modelling suggests that a large proportion of organisations—potentially as much as 89%–93%—may never adopt EBP. This result aligns with findings by Mills et al. (2019) that more than half of the area-based conservation initiatives they analysed were ultimately adopted by less than 30% of potential adopters. However, the true proportion of non-adopters is likely to be lower than our estimate, given that many organisations may have adopted EBP principles without explicitly referencing them in job adverts or may restrict EBP language to specific roles, such as 'evidence officers' (e.g. not for operations roles, unless it is contained in the description of the organisation). Consequently, job-advert prevalence probably better reflects the subset of positions directly involved in embedding evidence use rather than total organisational adoption. We also note that platform-specific criteria for posting job adverts, and any changes in those criteria over time, may have influenced the apparent prevalence of EBP-related roles, meaning our estimates should be interpreted as broad estimates and trends rather than precise values.

We also acknowledge the geographical skew of our job-advert dataset, dominated by UK postings (73%). Given that key EBP and EBC initiatives originated in the UK—such as the Centre for Evidence-Based Conservation, Collaboration for Environmental Evidence and Conservation Evidence project—the observed patterns may be mostly representative of UK trends. However, interestingly, EBP mentions were similar or lower (depending on using keywords or classifier estimates, respectively) in UK adverts than elsewhere, suggesting some broader international diffusion. Future work could test whether adoption correlates with uptake of other international job datasets or EBP-related frameworks, such as the Conservation Standards (2026), to assess how geographically widespread EBP principles have become.

A key question raised by our work is how much adoption is truly necessary for EBP to become a normalised feature of conservation practice. Diffusion of innovations theory implies that full universal uptake is unrealistic—and unnecessary—for systemic change. If EBP expands beyond innovators and early adopters into the early and late majority (roughly 70%–80% of organisations), it would likely be self-sustaining. Our best available estimates, even with their limitations, indicate the field of conservation and environmental management remains far from that threshold, but that we are heading in a positive direction. This highlights the importance of implementing strategies that actively support later adopters and address structural barriers rather than relying solely on passive diffusion of EBP.

4.2 | Communicating EBP, facilitating implementation, and avoiding 'evidence-washing'

Another important point requiring further investigation is the extent to which our proxy data reflect meaningful implementation of EBP. In some cases, EBP may be referenced in documents or job adverts without being routinely integrated into workflows and decision-making. Conversely, many practitioners may follow EBP principles without using the term, or may rely on alternative language for evidence use and learning. In our dataset, we observed a diversity of phrases related to being 'evidence-based' across practitioner-focused grey literature and more academic scientific literature, underscoring the lack of a shared vocabulary around EBP, evidence, and evidence use in conservation and environmental management. Building a common understanding of what constitutes meaningful EBP—among practitioners, policymakers and academics—will therefore be critical for supporting wider uptake.

Within this context, there is a risk that some organisations may claim to be evidence-based without systematically applying EBP principles, a phenomenon we refer to as 'evidence-washing', by analogy with greenwashing (de Freitas Netto et al., 2020). In large organisations, application of EBP may be uneven, with some teams engaging deeply with evidence while others do not, and communication or fundraising materials may overstate the extent of evidence use. In addition, different actors may hold genuinely divergent views about what EBP entails, leading some to believe they are following EBP whilst others would disagree.

For these reasons, we should be cautious about labelling organisations as evidence-washing. Public criticism could risk undermining trust, discouraging engagement and potentially harming funding for conservation organisations in general. Constructive mechanisms such as auditing, peer support or accreditation schemes—for example, building on the 'Evidence Champions' scheme (Smith et al., 2023)—may be more effective in encouraging organisations to reflect on their current practice, identify gaps and commit to incremental improvement.

Supporting a culture of evidence use requires both organisational and systemic changes (O'Connell et al., 2024). Conservation organisations often operate under time pressure and complexity, with decisions often framed as urgent 'crisis responses' where the perceived need to act quickly can outweigh the perceived feasibility of consulting or generating additional evidence. Discussions of EBP can implicitly assume that relevant evidence and the resources, capacity and skills to use it are readily available, which is often not the case. Taking a supportive stance means recognising these constraints and focusing on reducing the costs of using evidence, for example through accessible syntheses, practical guidance and embedded evidence roles.

At the same time, conservation organisations cannot afford not to be evidence-based if they are to maximise their impact under severe resource and time constraints in the face of the biodiversity extinction crisis. Learning systematically from past successes and failures is essential. However, this does not mean that every decision must be supported by a formal evidence review; such an expectation would be unrealistic and counter-productive, and may itself deter organisations from engaging with EBP. Instead, we can focus on helping organisations to triage when and how to use evidence—prioritising high-stakes or high-cost decisions where evidence can materially influence outcomes, whilst relying on lighter-touch approaches for routine practice and embedding this within existing adaptive management practices if present (Gillson et al., 2019).

Framing EBP as a staged process rather than an all-or-nothing status may also make it more approachable for later adopters—a key area to focus on given our findings suggest adoption is currently mainly among innovators and early adopters. Organisations should be encouraged to progress from initial awareness, through partial and targeted use of evidence in key decision areas, towards more comprehensive integration into planning, implementation and evaluation. Our findings also point to the need to ensure the enabling conditions for EBP are met to facilitate further adoption, such as easy and rapid access to synthesised evidence resources, training in evidence use and supportive organisational infrastructures and incentives (O'Connell et al., 2024).

Effective diffusion of EBP, underpinned by work to ensure its enabling conditions are set, will likely depend on combining top-down and bottom-up approaches. From the top down, boards, senior leaders and funders can signal expectations by incorporating EBP into key performance indicators, funding criteria or organisational strategies, including explicit requirements for appropriate evaluation and long-term management. From the bottom up, training, mentoring and communities of practice can build capacity among staff, helping them to integrate evidence into everyday workflows and adaptive management cycles, and merge EBP principles with local contexts and values. Initiatives such as the Conservation Evidence project and the Collaboration for Environmental Evidence already address the supply side by providing tools and syntheses. However, a parallel focus on change management inside organisations could help translate these resources into routine practice (Kadykalo et al., 2021; Sutherland, 2022).

This is already happening in several ways, for example, through workshops and meetings coordinated by Conservation Evidence (2024, 2026) to connect organisations embarking on embedding evidence use into their organisational practices (Smith et al., 2023; Tinsley-Marshall et al., 2022)—such organisations, including those on the 'Evidence Champions' scheme, can be seen as 'innovators' and 'early adopters' in terms of diffusion of innovations theory (Figure 1). The UK Wildlife Trusts have also created an Evidence Emergency project to assess how they can embed EBP more effectively and upskill their staff, including developing an Evidence Competency Framework and Self-assessment Tool (Sheffield & Rotherham Wildlife Trust, 2024)—a similar approach to Evidence Maturity Models in Evidence-based Policing (College of Policing, 2026). Meanwhile, funders (Al-Fulaij et al., 2025) are starting to require not only that applicants demonstrate they have used evidence to inform their proposals (e.g. that actions proposed are likely to be effective), but also to put funding and resources in place to facilitate appropriate, targeted evaluation and follow-up of actions by grantees. For instance, this includes supporting the generation and reporting of evidence where it may be lacking in the wider evidence base and not requiring evaluation of every aspect of a project, plus ensuring plans for long-term care and management are truly enacted.

These examples also highlight the critical importance of tailoring EBP implementation to different organisations, depending on their adoption stage, for it to succeed. Empirical work highlights that diffusion often does not follow a smooth progression through different adopter categories (from 'innovators' to 'laggards'), but can collapse or stall when innovations do not align or fit well with local tasks, incentives or institutional contexts (Greenhalgh et al., 2004; MacVaugh & Schiavone, 2010). Providing a general framework for implementing EBP is a crucial start, but we need to ensure that organisations continue receiving targeted support to help changemakers at all levels within organisations continue tailoring and applying evidence use to their unique organisational contexts.

4.3 | Future research directions

Our analyses provide an indirect but useful picture of how awareness and adoption of EBP is spreading, yet they cannot reveal how deeply EBP is embedded in day-to-day decisions within organisations. There is a clear need for more direct assessments of implementation, such as mixed-methods evaluations of how different forms of evidence are used in planning, management and monitoring (Lemieux et al., 2021; Stevens & Norris, 2022). Integrating insights from cognitive science on how practices spread and how to influence behaviours relating to EBP could also help to boost the effectiveness of its implementation and uptake (Papworth, 2017; Toomey, 2023). Building on approaches from other sectors, tools like competency frameworks or evidence-use audits could help diagnose organisational readiness for EBP and identify specific support needs (e.g. adapted EBP maturity models, standard scales for EBP and scorecards; College of Policing, 2026; Mohammadi et al., 2018).

Future work could also expand and refine the types of data used to track adoption, and investigate how different factors affect the uptake and depth of EBP implementation. In addition to job adverts and publications, relevant indicators might include the uptake of specific standards or frameworks that embody EBP principles (e.g. Conservation Standards, 2026), creation of dedicated evidence roles or units, or incorporation of explicit evidence requirements in funding calls. Longitudinal case studies of organisations at different stages of adoption would complement such indicators, including in-depth qualitative research to reveal how internal culture, leadership, funding structures and external networks shape the trajectory from initial awareness to routine, institutionalised EBP.

5 | CONCLUSIONS

Two decades on from the first calls for EBP in conservation and environmental management, our results suggest that awareness and uptake of EBP are increasing, but remain concentrated among a minority of organisations, mostly in the public and charity/not-for-profit sectors. Interpreted through diffusion of innovations theory, current patterns are consistent with an early-adopter phase and indicate that a substantial proportion of organisations may not yet, and may never, fully adopt EBP. This underscores the importance of targeted efforts that support and incentivise organisations to embed EBP in ways that are feasible and tailored to their contexts and constraints, whilst also monitoring for and constructively addressing potential 'evidence-washing'. Fostering a shared understanding of what meaningful EBP looks like in practice, and providing sustained support for organisations to progress towards it, will be essential if EBP and the movement for EBC is to realise its promise of improving conservation and environmental outcomes.

AUTHOR CONTRIBUTIONS

Alec P. Christie conceived the ideas and designed methodology. Alec P. Christie, Sophie Stenson and Nick Askew collected the data. Alec P. Christie analysed the data and led the writing of the manuscript. All authors contributed critically to the drafts and gave final approval for publication.

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CONFLICT OF INTEREST STATEMENT

The authors have no conflicts of interest.

PEER REVIEW

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DATA AVAILABILITY STATEMENT

Code and data to repeat analyses are available from Zenodo: https://doi.org/10.5281/zenodo.18619898 (Christie, 2026). Raw data including job-advert text and organisation names are unavailable due to this being commercial data, but processed, anonymised data used in modelling and plotting is available.

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SUPPORTING INFORMATION

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

Table S1. Search strings used to search grey and academic literature databases. To find the total number of articles on the topics of conservation and environmental management, we used only the search string with these associated keywords. We then combined the two search strings with the Boolean 'AND' operator to work out the number of articles in conservation and environmental management that mentioned keywords associated with evidence-based practice. The keywords used here for evidence-based practice are constrained to key direct terms used compared with Table S2 as the aim was to provide a conservative estimate.

Table S2. Keyword terms used to conduct feature engineering for the machine learning classifier. This set of keywords is an expansion of those keywords in Table S1 as the aim for the classifier was to provide a more liberal estimate and likely upper bound on the prevalence of evidence-based practice mentions.

Table S3. Results of Random Forest machine learning classifier validation at different thresholds using a 20% validation test subset (n = 26 positives, 64 negatives) to detect mentions of evidence-based conservation in job adverts. See methods for details.

Table S4. Frequency of terms mentioned in the scientific and grey literature databases. Search terms include non-hyphenated versions as per Table S1. Searches of each database were conducted between the years 2002–2025 inclusive.

Table S5. Sensitivity analysis to check whether excluding the incomplete year of job-advert data for 2025 affected our results. Table shows new results after removing data.

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