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Increasing the credibility of conservation plans through citizen science

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ABSTRACT

Plans for protected area systems (hereafter, prioritizations) need to identify cost-effective priority areas. They must also be supported by information that stakeholders value as credible. Although field observations are often considered highly credible, species distribution models are generally required to overcome sampling gaps and biases. Here we investigate how field observations collected through citizen science could help improve the credibility of prioritizations. Examining a case study in southern Ontario (Canada), we obtained expert survey and citizen science data for 14 plant species and fitted species distribution models. We generated conventional prioritizations following standard conservation planning approaches. We then generated prioritizations that allocated increasing budgets for representing species through priority areas with confirmed occurrences from expert surveys. We also generated prioritizations with confirmed occurrences from both expert surveys and citizen science. Assuming that greater coverage of confirmed occurrences conveys greater credibility, we assessed the putative credibility of prioritizations according to their ability to meet species representation targets with confirmed occurrences. We found trade-offs between minimizing the cost of prioritizations and maximizing their putative credibility. Although such trade-offs were most acute under limited budgets, prioritizations generated with confirmed occurrences from expert surveys and citizen science achieved a moderate increase in putative credibility for only a minor increase in cost. Additionally, our results showed that prioritizations generated with expert surveys and citizen science had greater putative credibility than those generated with expert surveys alone. By considering the perceived credibility of supporting data, conservation planning exercises may achieve greater approval by stakeholders.

1. Introduction

Protected areas are urgently needed to safeguard biodiversity (Watson et al., 2014). Because the resources for conservation are limited, plans for establishing and expanding protected areas (hereafter, prioritizations) must achieve conservation objectives for minimal cost (Giakoumi et al., 2025). Additionally, because stakeholder acceptance is vital for implementation (Knight et al., 2008; Nel et al., 2015; Araújo, 2025), prioritizations must also be supported by sources of information that stakeholders perceive to be salient (pertinent and timely), credible (accurate and trusted), and legitimate (unbiased and fair) (Cash et al., 2003; Cook et al., 2013; Buschke et al., 2023). Although a wealth of biogeographical data are available to inform priority setting (e.g., Boakes et al., 2010; Lumbierres et al., 2022), sources of information that stakeholders value as highly credible – such as expert field surveys – may not be available across all candidate priority areas for all species of interest (Theobald et al., 2000; Balram et al., 2004). As such, prioritizations may need to compromise between reducing costs, satisfying conservation objectives, and ensuring that priority areas are identified by highly credible information (Kareksela et al., 2018; Berio Fortini et al., 2024). Thus there has been growing interest in understanding how to cost-effectively maximize credibility (Theobald et al., 2000; Balram et al., 2004; Berio Fortini et al., 2024).

Field observations often are perceived as highly credible sources of information by conservation managers and practitioners (e.g., Kuiper et al., 2023; Berio Fortini et al., 2024). Indeed, such observations have been used to identify critical habitats for the protection of threatened species in Australia, Canada, and the United States (Camaclang et al., 2014). However, field observations are rarely complete and spatially biased sampling procedures may cause populations to be overlooked during priority setting (Pressey, 2004; Rondinini et al., 2006). To overcome this limitation, field observations are commonly used to fit species distribution models and, in turn, predict the complete spatial distribution of species across a region (e.g., Chowdhury et al., 2023;

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Binley et al., 2025). Although such models may be able to predict species' occurrences with a high degree of accuracy, stakeholders may not value them as highly credible sources of information (Hunka et al., 2012; Villero et al., 2016). As such, recent work has started to preferentially identify priority areas that contain field observations to maximize credibility with stakeholders (Berio Fortini et al., 2024).

Citizen science is a valuable source of field observations for biodiversity (reviewed in McKinley et al., 2017). Briefly, citizen science (also referred to as community or participatory science) is the participation of the public in scientific research, and often involves collecting or analyzing data (Kelly et al., 2019). Platforms for hosting citizen science projects – such as eBird (https://ebird.org) and iNaturalist (https://www.inaturalist.org) – provide millions of field observations for species worldwide (Di Cecco et al., 2021; La Sorte et al., 2024). They also have review procedures for quality control (Sullivan et al., 2014; White et al., 2023). For example, an iNaturalist observation may be classified as "Research Grade" if it has a valid date, location, photo or sound recording, does not pertain to a captive (or cultivated) organism, and has been reviewed by the community (iNaturalist, 2024). Despite the fact that citizen science observations tend to be biased towards more accessible areas (Mair and Ruete, 2016), they provide many observations for threatened species (Soroye et al., 2022; La Sorte et al., 2024). Although citizen science may be viewed as less credible than professional observations by some stakeholders (Vann-Sander et al., 2016; Suškevičs et al., 2021), citizen science could potentially help improve the credibility of prioritizations because it provides direct observations that stakeholders often value as highly credible (Aceves-Bueno et al., 2015; Kelly et al., 2019).

Citizen science data can help improve the accuracy of data that underpin priority setting (Forti et al., 2024; Binley et al., 2025). For example, records from social media posts and citizen science platforms have been used – in combination with those from scientific data repositories – to improve the accuracy of species distribution models for subsequent prioritization (e.g., Chowdhury et al., 2023; Binley et al., 2025). Participatory mapping techniques have also been used to accurately digitize stakeholder preferences and, in turn, help prioritizations achieve stakeholder objectives (Kockel et al., 2020). In addition to improving credibility through accuracy, citizen science can also help improve credibility through trust (Kelly et al., 2019). For instance, recent work has used citizen science to improve the credibility of prioritizations by ensuring that priority areas represent a species of conservation concern in locations that are supported by stakeholder knowledge (Borges et al., 2025). Yet the trade-offs associated with this remain poorly understood.

Here we examine how citizen science could help improve the consideration of credibility in prioritizations. Using a case study in southern Ontario, we obtained expert survey and citizen science data for 14 imperiled plant species (Supplementary Material, Table S1). To characterize the spatial distribution of each species, we fitted integrated species distribution models and used the expert survey and citizen science data to augment model predictions. This provided the predicted spatial distribution of each species. Next, we generated conventional prioritizations that focused on minimizing total cost and meeting conservation objectives for species representation based on the species' predicted spatial distributions. We then generated a set of expert-based prioritizations that – in addition to considering total cost and species representation – maximized representation of confirmed occurrences from expert surveys. In a similar manner, we generated a set of combined data prioritizations that maximized representation of confirmed occurrences from expert surveys and citizen science. To investigate trade-offs between credibility and the implementation cost of a prioritization, we generated multiple expert-based and combined data prioritizations under a range of different budgets.

2. Materials and methods

2.1. Study system

Our study encompassed 23 counties and regional municipalities in southern Ontario, Canada. Within this region, we examined 14 imperiled plant species that are recognized by provincial and federal authorities (Table S1). These species are facing mounting pressure from commercial development and urbanization, and urgently require habitat protection (McCune et al., 2013; McCune and Morrison, 2020). Based on the species' life forms and statistics reported by Chen et al. (2013), we inferred estimates for the sensitivity (true positive rate) of expert surveys and citizen science observations (Table S1). Note that we assume expert surveys and citizen science observations have an equal sensitivity, because we considered only "Research Grade" citizen science observations in our analysis. To standardize spatial analyses, we created a spatial grid (comprising 23636 cells at a 1.5 km resolution) across the study area to serve as candidate planning units (Fig. 1). We chose the scale of the spatial grid based on a compromise between the spatial accuracy of the datasets considered in the analysis (see below) and computational burden. Because our study focuses on terrestrial species, we obtained land cover data (30 m resolution) (Agriculture and Agri-Food Canada, 2019) and excluded planning units that were entirely covered by waterbodies from subsequent analysis. We performed all analyses with the *R* statistical computing environment (version 4.4.1; R Core Team, 2024). We completed spatial analyses with the *sf* and *terra R* packages (Pebesma, 2018; Hijmans, 2024), and data processing and visualization with the *tidyverse* family of *R* packages (Wickham et al., 2019).

2.2. Data

We obtained expert survey data for the study species from previous ecological surveys (Supplementary Material, Table S2) (McCune, 2016; McCune et al., 2020; Rosner-Katz et al., 2020). Briefly, these data comprised 282 surveys of one-hectare forest plots. Because they were collected by expert botanists as part of systematic and exhaustive surveys in which they aimed to record all vascular plant species present in each plot, these data provide detections and non-detections for each study species at each sampled locality. However, we acknowledge that non-detections could represent false absences in some cases (e.g., for spring ephemeral species at sites surveyed later in the summer). To supplement the surveys, we obtained observation records from the Natural Heritage Information Centre (NHIC) of Ontario, and additional records currently held in the "central holdings" database prior to being added to the official NHIC database (Government of Ontario, 2018). Despite the fact that these observation records have been vetted by expert botanists, they may not have been collected by expert botanists and so we do not assume that they provide non-detections. To help ensure consistent spatial precision between the surveys and NHIC observation records, we excluded NHIC observation records with a spatial uncertainty greater than 100 m. Additionally, to avoid duplication issues, we excluded NHIC observations recorded in the same plot as detections in the ecological survey data. For brevity, we refer to the combined ecological survey and NHIC observation dataset as "expert survey data". After assembling these data, we retained detections and non-detections within the study area for subsequent analysis (see Supplementary Material, Fig. S1 and Table S3).

We obtained citizen science data for the study system. To achieve this, we retrieved "Research Grade" observations from the iNaturalist platform for all plant species within Ontario, Canada (via the Global Biodiversity Information Facility; GBIF.Org User, 2024). Although such observations may not be highly accurate for particular taxa (e.g., McMullin and Allen, 2022), previous work has shown that they can be accurate for flowering plant species (White et al., 2023). To help ensure data quality, we excluded citizen science observations with fewer than 5

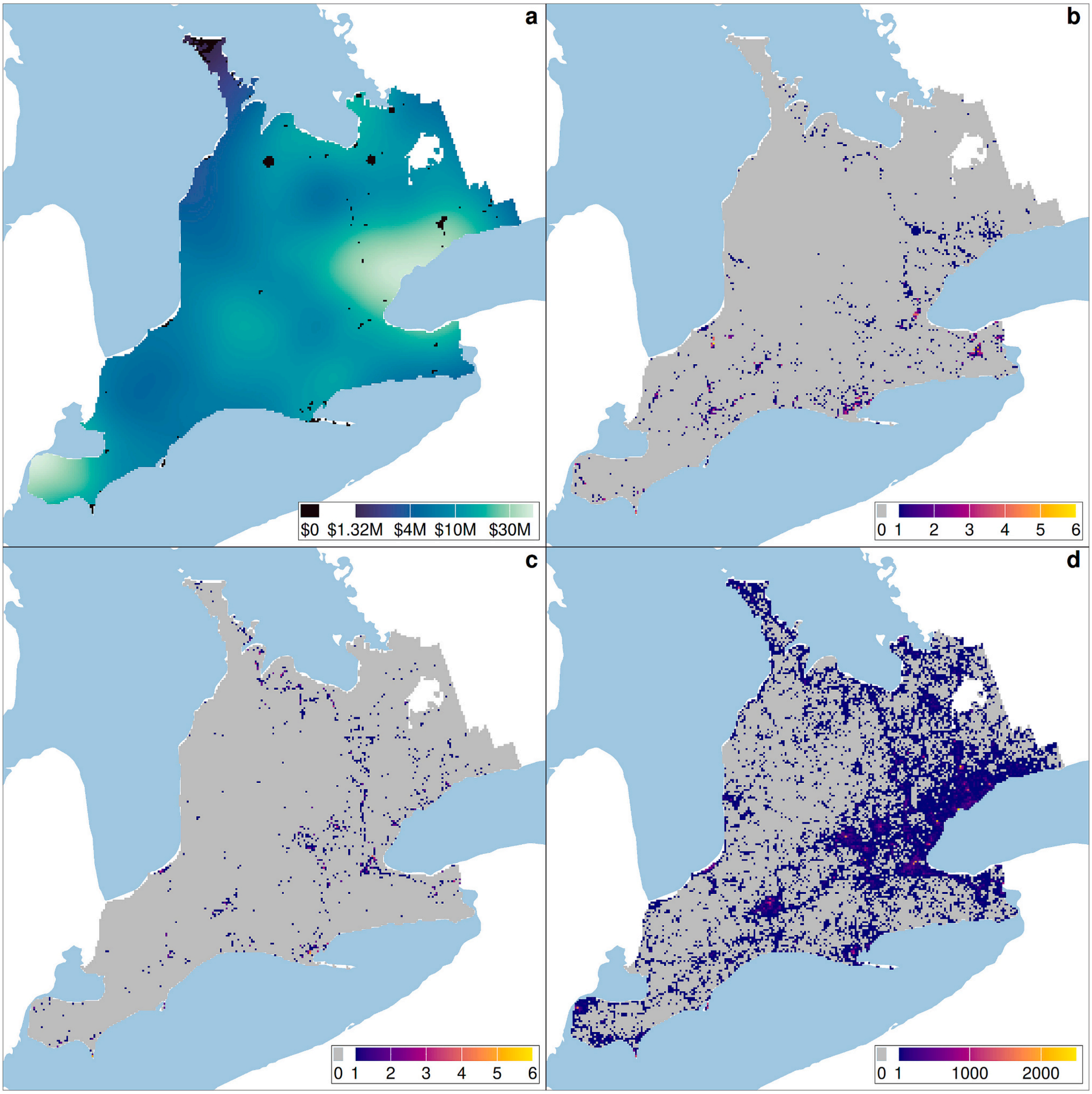

Fig. 1. Maps show planning units and their (a) spatially interpolated land acquisition costs (CAD), (b) species richness based on confirmed occurrences by expert surveys (i.e., number of the 14 study species present), (c) species richness based on confirmed occurrences by citizen science observations, and (d) sampling effort by citizen scientists. Note that planning units associated with zero cost values were covered by existing protected areas.

decimal places precision for geodetic coordinates, spatial uncertainty exceeding 1 km or reported as invalid, or recorded before 1980. We chose these data quality criteria because they would exclude records that lack suitable spatial precision, or historical records that may be out of date. Because citizen scientists may not conduct exhaustive surveys, we assume that these data provide detections only – and do not provide non-detections – for study species at sampled localities. To characterize spatial biases in sampling effort, we recorded the total number of observations within each planning unit (Fig. 1d). We then prepared these data for subsequent analysis by excluding observations that were collected outside the study area or did not correspond to the study species (see Supplementary Material, Fig. S2, Tables S2 and S3). Note that none of the remaining citizen science observations were duplicated in the expert survey data.

We obtained data to characterize environmental conditions. Specifically, we obtained 19 bioclimatic variables (30 arc resolution; Supplementary Material, Table S4) (Karger et al., 2017, 2021). We also obtained soil data (Agriculture and Agri-Food Canada, 2018) and considered the following variables to characterize edaphic conditions: oxygen capacity, acidity, clay percentage, and available water holding capacity (90 m resolution, corresponding to a depth of 60 cm). We then reprojected and resampled these data to match the spatial grain of the planning units. Next, we excluded highly correlated variables prior to model fitting to avoid multi-collinearity issues. To achieve this, we excluded highly correlated variables based on a Spearman's rank correlation analysis and a stepwise procedure involving variance inflation factors (VIF) (with the *ibis.iSDM* and *usdm R* packages respectively; Naimi et al., 2014; Jung, 2023). In particular, we used a cutoff threshold of 0.8 for the correlation analysis and a VIF threshold of 10 (per Naimi et al., 2014; Díaz-Vallejo et al., 2024). Thus we obtained a set of six bioclimatic and four soil variables (hereafter, environmental data) for subsequently fitting species distribution models (Supplementary Material, Fig. S3).

We obtained data to inform reserve selection. To account for existing protected areas, we obtained the boundaries of protected areas from the World Database on Protected Areas (IUCN and UNEP-WCMC, 2024). We then cleaned these data following standard practices (with the *wdpar R* package; Hanson, 2022), overlaid them with the planning units, and subsequently treated planning units that had at least half their total area covered by protected areas as formally protected (Fig. 1a). We also estimated land acquisition costs (following Hanson et al., 2022). To achieve this, we obtained property valuation data (January 2016) from the GeoWarehouse software (Teranet., 2018) and used thin plate regression splines to spatially interpolate values for each planning unit (with the *fields R* package; Nychka et al., 2021). To improve performance (Supplementary Material, Table S5), we $\log_{10}$ transformed property values prior to interpolation and subsequently back-transformed predictions. Because the property values were expressed as cost per hectare, we then multiplied property values by the size of each planning unit to estimate total acquisition costs (Fig. 1a).

2.3. Species distributions

We used an auxiliary approach for fitting integrated distribution models for the study species (see Supplementary Material, Appendix S1 for detailed explanation). Briefly, integrated distribution models are a type of species distribution model that is designed to accommodate multiple data types (Fletcher et al., 2019). Because the expert survey (i.e., presence-absence data) and the citizen science data (i.e., presence-only data) were sampled following different protocols (as described in the Data section), it was important to use an integrated distribution modeling approach. In particular, we used an auxiliary approach (sensu Fletcher et al., 2019). Broadly speaking, for a given species, this approach involves (i) fitting an initial species distribution model based on one occurrence dataset (i.e., citizen science data in our case), (ii) generating predictions from the initial model, (iii) fitting a subsequent species distribution model based on another occurrence dataset (i.e., expert survey data in our case) with the generated predictions from the initial model as a predictor variable (along with other predictor variables), and (iv) generating predictions from the subsequent model. Below we provide more detail on the model fitting procedures.

We fitted species distribution models for the study species (1.5 km resolution) (see Appendix S1 for details). To begin with, we fitted a set of species distribution models (with the *MaxEnt* software and *ENMeval R* package; Kass et al., 2021; Phillips et al., 2024) to the citizen science observations with the environmental data as predictor variables (Supplementary Material, Fig. S4 and Table S6). After fitting these models, we used them to predict environmental suitability estimates for each planning unit (Supplementary Material, Table S7). We then fitted a secondary set of species distribution models (i.e., integrated species distribution models) with extreme gradient boosting techniques (with the *xgboost R* package; Chen et al., 2024) to the expert survey data with the environmental data and environmental suitability predictions from the previous models as predictor variables (Supplementary Material, Fig. S5 and Table S8 for further details). Note that all *MaxEnt* and gradient boosted models were fitted with five-fold cross-validation (separately). By employing this approach, the integrated species distribution models were informed by both the expert survey and citizen science datasets, whilst ensuring that our model fitting procedures were well suited to the sampling protocols that underpin each dataset (Phillips et al., 2017; Muñoz-Mas et al., 2019). After fitting the integrated species distribution models, we evaluated their sensitivity (true positive rate), specificity (true negative rate), and true skill statistic (TSS) based on the test folds (Table S7). We employed the TSS statistic because it balances the sensitivity and specificity metrics. We subsequently used these metrics to characterize the spatial distribution of species whilst accounting for model uncertainty.

We characterized the spatial distribution of each species with the best information available (hereafter, predicted spatial distribution) (Supplementary Material, Fig. S6). Although the integrated species distribution models had sufficient predictive performance (Table S7), many planning units had multiple detections or non-detections that could greatly reduce uncertainty when estimating the probability that particular species are present within them. This means that, for some planning units, the best source of information for inferring the presence or absence of a particular species within them might be the integrated species distribution models and, for other planning units, the best source of information might be the expert survey and citizen science data instead. As such, we used a Bayesian approach to estimate the probability that each species is present within each planning unit based on either the combined expert survey and citizen science data or the integrated species distribution models, depending on which source of information had the greatest ability to reduce uncertainty (see Supplementary Material, Appendix S2 for further details). Note that we did not calculate a joint likelihood by combining expert surveys, citizen science observations, and integrated species distribution model predictions together, because the expert surveys and citizen science observations are not independent of the integrated species distribution models.

2.4. Spatial prioritizations

We generated conventional prioritizations that exemplify typical approaches for priority setting (see Supplementary Material, Appendix S3 for mathematical formulation). These prioritizations considered only the predicted spatial distributions for characterizing species distributions. Thus they did not explicitly consider confirmed occurrences when identifying places selected for prioritization (hereafter, priority areas). In particular, we generated four conventional prioritizations following the minimum set formulation of the reserve selection problem (Rodrigues et al., 2000). We generated each of these four prioritizations following a different target setting scenario, where prioritizations were generated with representation targets to ensure that priority areas covered at least 5 %, 10 %, 20 %, and 30 % (respectively) of the species' predicted spatial distributions (separately). These species representation targets were chosen to explore a range of scenarios that represent various levels of ambition and investment by local governments (Carvalho et al., 2010). We generated all of these prioritizations with land valuation estimates to parametrize planning unit costs, and locked in planning units covered by existing protected areas. After generating the conventional prioritizations, we computed their total costs and used this information to help specify budgets in subsequent prioritizations.

We then generated prioritizations that aimed to maximize credibility by explicitly considering confirmed occurrences during priority setting. To achieve this, we used a multi-objective hierarchical mixed integer programming approach (see Supplementary Material, Appendix S4 for mathematical formulation). Briefly, our approach involved the minimum shortfall formulation of the reserve selection problem (Jung et al., 2021). This formulation was used to help ensure that species' representation targets were met through selecting planning units with confirmed occurrences, whilst ensuring that the cost of the prioritization does not exceed a pre-specified budget. Additionally, to ensure prioritizations met the species' representation targets – either entirely through planning units with confirmed occurrences or a combination of planning units with and without confirmed occurrences – our approach also involved adding linear constraints parametrized with the species' predicted spatial distributions. With this approach, we generated a set of prioritizations based on maximizing credibility according to the expert surveys (hereafter, expert-based prioritizations) and a second set of prioritizations according to expert surveys and citizen science observations (hereafter, combined data prioritizations). Similar to the conventional prioritizations, we generated these two sets of prioritizations under four different target setting scenarios (with the same target thresholds as described previously). For each target setting scenario, we generated the two sets of 35 prioritizations according to incremental budgets ranging from a 1 % increase to a 35 % increase over the total cost of the conventional prioritization generated following the same target setting scenario. We generated all of these prioritizations – similar to the conventional prioritizations – with land valuation estimates to parametrize planning unit costs, and locked in planning units covered by existing protected areas.

All prioritizations were generated with the *prioritizr R* package (version 8.0.4; Hanson et al., 2025b). In particular, each prioritization identified priority areas for protection using binary values (see Appendix S3 and S4). Optimization procedures were completed with the *Gurobi* software (version 12.0.2; Gurobi Optimization LLC, 2025) with a 0.5 % optimality gap. Note that all prioritizations are comparable, because they were generated with the same cost data, locked in and out constraints, and were constrained to meet each species' representation target (i.e., either through targets with the minimum set formulation or linear constraints with the minimum shortfall formulation).

2.5. Statistical analysis

We developed a metric to assess the credibility of a prioritization based on a set of confirmed occurrences (hereafter, referred to as putative credibility). For a given prioritization, this metric involved calculating the percentage of each species' representation target that was met through priority areas (i.e., selected planning units) with confirmed occurrences for that particular species and then calculating the average of these species-specific percentages (see Supplementary Material, Appendix S5 for mathematical description). We designed this metric to account for the fact that a confirmed occurrence for a particular species only conveys credibility for that particular species (Berio Fortini et al., 2024), consider all species in the prioritization, and maintain consistency with the multi-objective hierarchical mixed integer programming approach used to formulate prioritizations that maximize credibility (see Appendix S5 for detailed explanation). Additionally, this metric is easily interpretable with a value of 0 % corresponding to a prioritization that does not represent a single species in any planning unit with a confirmed occurrence for that species, and a value of 100 % corresponding to a prioritization that meets all of the species' representation targets through priority areas with confirmed occurrences for each species.

We evaluated the prioritizations with the putative credibility metric. When calculating this metric, we evaluated the conventional prioritizations based on confirmed occurrences from expert surveys. We also evaluated these prioritizations based on confirmed occurrences from expert surveys and citizen science. Additionally, we evaluated the expert-based prioritizations based on confirmed records from expert surveys, and the combined data prioritizations based on confirmed records from expert surveys and citizen science. Although another metric for assessing credibility could simply involve calculating the percentage of priority areas that had at least one confirmed occurrence for any given species, such a metric does not consider species representation targets or which confirmed occurrences relate to which species. Because all of the prioritizations are directly comparable with each other, for a given target setting scenario, we can directly compare the prioritizations to examine trade-offs between cost (per their land-acquisition budget for protected area establishment), putative credibility, and the source of confirmed occurrences used to evaluate putative credibility.

3. Results

We obtained 6481 confirmed occurrences across all expert surveys and citizen science observations (Table S1). In total, 4.3 % of the planning units had at least a single confirmed occurrence from expert surveys within them, and 3.57 % of the planning units had at least a single confirmed occurrence from citizen science within them. Most species had a relatively small percentage of their predicted spatial distribution associated with confirmed records. Species had, on average, 1.52 % (ranging from 0.49 % to 3.75 %) of their predicted spatial distribution associated with confirmed records from expert surveys. Species also had, on average, 0.87 % (ranging from 0.09 % to 3.25 %) of their predicted spatial distribution associated with confirmed records from citizen science. Because there was considerable overlap in confirmed records from the expert surveys and citizen science, combining these two data sources did not substantially increase the percentage of species' predicted spatial distributions associated with confirmed occurrences (Fig. 1). For instance, when adding confirmed records collected through citizen science to the expert surveys, the percentage of species' predicted spatial distributions associated with confirmed records only increased from, on average, 1.52 % to 2.01 % (Supplementary Material, Fig. S7, Table S9).

Prioritizations exhibited a trade-off between minimizing cost and putative credibility (Fig. 2). Indeed, this trade-off was especially acute under smaller representation targets (Fig. 2a and b). For example, the conventional prioritization generated with 5 % species representation targets had a putative credibility – as evaluated with confirmed records from expert surveys and citizen science – of 6 % (Fig. 2a, gray point). In other words, under this prioritization, 6 % of each species' representation target was met, on average, through priority areas with confirmed occurrences from expert surveys and citizen science. By explicitly considering confirmed occurrences from expert surveys and citizen science during optimization, applying the same 5 % species representation targets, and affording a 1 % increase in budget (i.e., a total budget of $3128.11 M CAD), the combined data prioritization had a putative credibility of 10.45 % (Fig. 2a, blue point with smallest budget). Additionally, by affording a 35 % increase in budget (i.e., a total budget of $4181.13 M CAD) (Fig. 2a, blue point with greatest budget), this further increased to a putative credibility of 23.42 %—representing a 290.35 % increase over the conventional prioritization. Thus confirmed occurrences may be especially helpful in improving the credibility of prioritizations when limited resources are available. Although the conventional prioritizations could have had relatively high putative credibility because places with confirmed records tend to have a relatively high probability of occupancy, these results show that explicitly considering confirmed occurrences as an objective during optimization can increase putative credibility.

The combined data prioritizations (Fig. 2, blue lines) had, on average, 1.94 % greater putative credibility than the expert-based prioritizations (Fig. 2, orange lines). In other words, the putative credibility of prioritizations based on confirmed occurrences from expert surveys and citizen science was greater than that of prioritizations based on confirmed occurrences for expert surveys alone. In particular, increases in putative credibility were greatest for prioritizations generated with relatively small species representation targets (Fig. 2a and b). For example, when considering prioritizations generated with 5 % species representation targets and a total budget of $3128.11 M CAD (Fig. 2a), the expert-based prioritization had a putative credibility of 8.45 % (Fig. 2a, orange point with smallest budget). Meanwhile, when considering the same representation targets and budgetary constraint, the combined data prioritization had a putative credibility of 10.45 % (Fig. 2a, blue point with smallest budget). These modest increases are likely due, in part, to the fact that adding confirmed records collected through citizen science to expert surveys did not substantially increase the percentage of species' predicted spatial distributions associated with confirmed records. Although such modest increases did not represent substantial increases in putative credibility, they may yet still be useful in decision making contexts where credibility is critical for achieving stakeholder consensus.

Prioritizations generated with smaller species representation targets

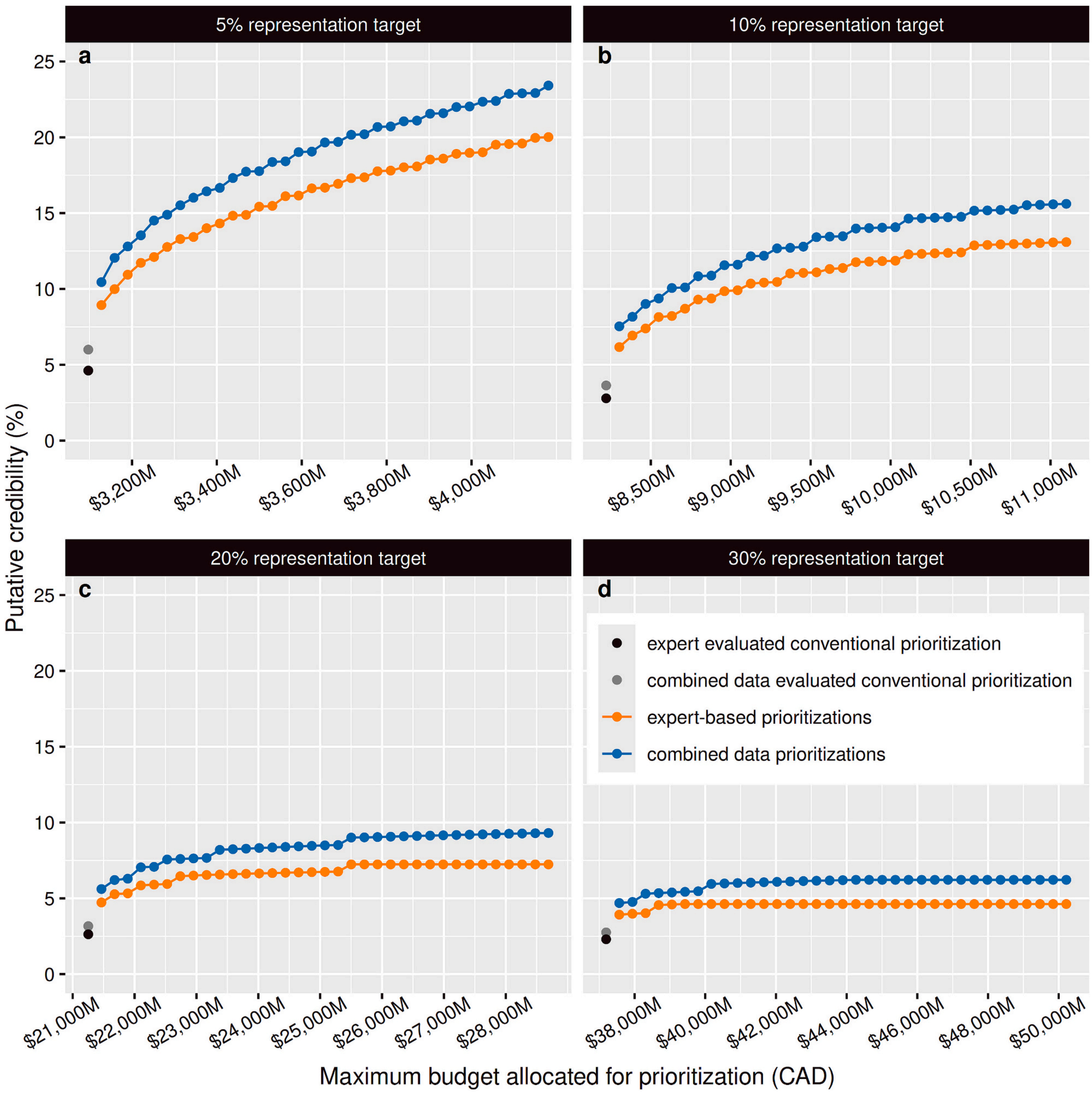

Fig. 2. Trade-offs between the putative credibility of a prioritization and the total budget allocated for generating it. Because a prioritization should ideally minimize costs and maximize credibility, positive relationships between these two metrics indicate trade-offs between them. Data show conventional prioritizations and their putative credibility evaluated based on confirmed occurrences from expert surveys (i.e., expert evaluated conventional prioritizations) and evaluated based on expert surveys and citizen science (combined data evaluated conventional prioritization). Additionally, data show prioritizations that maximized credibility based on confirmed occurrences from expert surveys (i.e., expert-based prioritizations), and expert surveys and citizen science observations (i.e., combined data prioritizations). Panels correspond to prioritizations generated with different species representation target thresholds, and prioritizations within the same panel are directly comparable because they all meet the same minimum representation targets for each species. Points denote the putative credibility computed for a given prioritization based on all study species, and lines connect points to illustrate trends.

tended to have greater putative credibility than those with greater targets (e.g., compare Fig. 2a and d). This is likely due to the fact that putative credibility was evaluated, in part, based on a percentage of each species' representation target. As such, a prioritization with greater representation targets would require a greater number of priority areas associated with confirmed occurrences to achieve the same putative credibility as a prioritization with smaller representation targets. Because most species only had a small percentage of their predicted spatial distribution associated with confirmed occurrences (e.g., species had, on average, 2.01 % of their predicted spatial distributions associated with confirmed occurrences from expert surveys or citizen science), prioritizations with 20 % and 30 % representation targets were only able to achieve relatively a low putative credibility. Indeed, even when relatively large budgets were considered for increasing credibility, it was not possible to increase the putative credibility of prioritizations generated with these representation targets beyond a certain point because all known occurrences were represented (i.e., see asymptotic relationships in Fig. 2c and d).

4. Discussion

Conservation plans based on credible data are more likely to be supported by stakeholders and implemented by managers (Cook et al., 2013; Nel et al., 2015). We examined the ability for expert surveys and citizen science to provide confirmed occurrences to improve the credibility of prioritizations. Our results show that explicitly considering field observations collected through expert surveys can substantially increase the ability of a prioritization to meet species' representation targets through locations with confirmed occurrences. Moreover, by considering field observations collected through citizen science – in addition to expert surveys – it is possible to further increase the ability of a prioritization to meet species' representation targets through locations with confirmed occurrences. Although our analyses revealed trade-offs between the putative credibility of prioritizations and their costs, it may be possible to greatly increase their credibility for only a minor increase in cost.

We found that it may be possible to increase the credibility of prioritizations by considering additional confirmed occurrences from citizen science. Within a prioritization, priority areas supported by confirmed occurrences may be viewed as more credible (Berio Fortini et al., 2024). Although citizen science observations are often biased towards locations with greater accessibility and human population density (Mair and Ruete, 2016; La Sorte et al., 2024), our results add to the growing body of literature showing how citizen science can inform decision making for threatened species (Soroye et al., 2022; Chowdhury et al., 2023). Additionally, we found that considering field observations collected through citizen science provided the greatest benefits over relying solely on expert surveys under relatively small representation targets and budgets. This is especially pertinent because real-world conservation planning exercises often have limited budgets (Halpern et al., 2006). While citizen science observations provided only a small increase in the percent of each species' distribution associated with confirmed occurrences in our work, they still improved the credibility of prioritizations, which suggests that even limited citizen science datasets may help improve the credibility of conservation plans.

Our results suggest that representing species in priority areas with confirmed occurrences – obtained through expert surveys or citizen science – may be a cost-effective strategy for increasing the credibility of prioritizations. This is because field observations are often considered highly credible (Rondinini et al., 2006; Kuiper et al., 2023), and we found that it was possible to increase the percent of species' representation targets met through priority areas with confirmed occurrences for only a minor increase in cost. Indeed, recent work by Berio Fortini et al. (2024) demonstrated that including field observations in a real-world conservation planning exercise was an effective strategy for obtaining buy-in and reaching consensus with stakeholders. Although the cost of conducting new surveys can be considerable when limited budgets are available (Raymond et al., 2020), the cost of preparing existing confirmed records for inclusion in prioritization analyses may be negligible. As such, decision makers may need to carefully weigh the potential benefits of collecting new confirmed records (Hanson et al., 2022). Future studies could build on our work to examine spatial drivers of species richness in threatened plants, or generate prioritizations that explicitly consider trade-offs in credibility among multiple different stakeholder groups.

Although our approach could help improve the credibility of prioritizations, we caution that it has the potential to introduce undesirable biases into priority setting. For example, occurrence data – especially citizen science data – may be more prevalent in disturbed areas due to greater accessibility (Boakes et al., 2010; La Sorte et al., 2024), and so preferentially selecting priority areas that have confirmed occurrences may bias prioritizations towards disturbed locations where populations may be less viable. Indeed, one of the advantages that species distribution models have over occurrence data is that such models can help mitigate sampling bias in priority setting (Rondinini et al., 2006). To help avoid such undesirable biases, precautionary measures could be implemented during priority setting. For example, highly degraded planning units could be locked out from selection (e.g., Powers et al., 2022), or planning unit costs could reflect both acquisition and restoration costs so that the optimization process can account for the fact that highly degraded areas require more intensive management (e.g., Lentini et al., 2013). Additionally, species distribution models could be fitted with predictor variables pertaining to anthropogenic pressures so that degraded areas have lower predicted occupancy (e.g., Chauvier et al., 2021) and, in turn, prioritizations cannot satisfy representation targets entirely through the selection of degraded areas.

Our methodology underscores the flexibility of systematic conservation planning for incorporating a multitude of criteria for priority setting (Rodrigues et al., 2000; Hanson et al., 2025b; Giakoumi et al., 2025). In addition to considering confirmed occurrences, our methodology also considered land acquisition costs, existing protected areas, feasibility of protected area establishment, species distribution models, and representation targets to ensure adequate coverage of species. To achieve this, we used a multi-objective hierarchical mixed integer programming approach for generating prioritizations because it enabled us to explicitly account for all these criteria and identify solutions that are guaranteed to be near-optimal—which is important for understanding trade-offs between competing criteria (Álvarez-Miranda et al., 2020). We also note that our approach could be extended to consider additional criteria that have "legitimating power" (sensu Kareksela et al., 2018) for stakeholders (e.g., presence of threatened species or high species diversity; Theobald et al., 2000; Cook et al., 2012; Kareksela et al., 2018). Indeed, exploring trade-offs between credibility and legitimacy in conservation decision making, and strategies for resolving conflicts between these considerations would be a fruitful area for future research. Furthermore, instead of considering the probability of occurrence for species within a given planning unit, our analysis could be extended to consider the population abundance or viability of each species with each planning unit (e.g., Bino et al., 2015). Although previous studies have emphasized limitations of mixed integer programming and related approaches – because they are unable to accommodate particular criteria that require complex nonlinear equations (Berio Fortini et al., 2024) – we show that these approaches can be particularly well suited for conservation planning exercises that do not consider such criteria.

We investigated the ability of field observations collected through citizen science to help improve the credibility of conservation plans. Our study considered citizen science from the long-standing iNaturalist platform with optimization procedures for promoting credibility. While research has demonstrated that citizen science can produce reliable data, procedures for ensuring accuracy are crucial (e.g., procedures for classifying iNaturalist observations as Research Grade) (Aceves-Bueno et al., 2015). However, such perceptions of credibility may not be universally held among decision makers and stakeholders engaged in conservation planning. Although our findings demonstrated the potential benefits of including citizen science data, the extent to which such data are viewed as both credible and legitimate by conservation practitioners would make a productive area for future research (Conrad and Hilchey, 2010). As such, we recommend engaging early with stakeholders to better understand what sources of information have the greatest credibility for them (Knight et al., 2008). By explicitly incorporating information on the perceived credibility of data sources into priority setting, conservation planning exercises may have greater success in implementation (Kareksela et al., 2020; Berio Fortini et al., 2024).

CRediT authorship contribution statement

Jeffrey O. Hanson: Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Jenny L. McCune:** Writing – review & editing, Resources, Methodology, Data curation, Conceptualization. **Tim Alamenciak:** Writing – review & editing, Methodology, Conceptualization. **Joseph R.**

Bennett: Writing – review & editing, Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare that there are no conflicts of interest.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.biocon.2025.111552.

Data availability

Code are archived in the Zenodo digital repository (Hanson et al., 2025a). This repository also contains a description of the study following the Overview and Design Protocol for Systematic Conservation Planning (Jung et al., 2025). All data were obtained from previously published sources or data repositories. In particular, species location data and property valuation data were not publicly archived because they contain sensitive information. Following appropriate training and signing of data sharing agreements with provincial authorities (contact NHICrequests@ontario.ca), species location data can be accessed from the Natural Heritage Information Centre of Ontario, of the Ontario Ministry of Natural Resources and Forestry. Property valuation data are accessible through the GeoWarehouse software (https://www2.geowarehouse.ca) or the appropriate land registry office (https://www.ontario.ca/page/land-registry-offices-lro).

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