Title: Climate vulnerability assessment framework choice influences species prioritization and prediction of population decline

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Abstract

Climate change vulnerability assessments (CCVAs) are regarded as an essential strategy to conservation strategies but are rarely used to inform conservation planning and prioritize species for management and adaptation. The main factor inhibiting its use is the challenge of combining exposure, sensitivity, and adaptive-capacity variables and, especially, of evaluating the ability of frameworks to predict species decline. This raises a fundamental challenge for conservation science: can climate vulnerability reliably identify species of conservation concern before widespread declines occur? Using extensive long-term monitoring data for 236 breeding bird species in North America, we compared a Trait-based Vulnerability Index (TVI), which combines variables into a fixed-weight composite index, with a Climate Vulnerability Model (CVM) that estimates the relative contribution of the same variables statistically. The two approaches showed limited agreement in the species identified as highly vulnerable (35.6% overlap), indicating that vulnerability estimates differed substantially among assessment frameworks. This divergence varied by guild and biome, with the greatest disagreement between frameworks found for seabirds, and CVM outperforming TVI in most biomes except for grassland-associated species. Exposure variables, particularly projected habitat loss and cumulative threat burden, outperformed intrinsic traits in predicting both climate-change threat listings and observed population decline. Species assigned higher model-based climate vulnerability were significantly more likely to exhibit long-term population declines, whereas sensitivity and adaptive-capacity traits provided comparatively little additional predictive information. Our study provides a rare empirical evaluation of climate vulnerability assessments and their ability to identify species experiencing biological decline. Our results suggest that different vulnerability assessments can lead to different conservation priorities, indicating that

additional work is needed to improve and validate climate-risk frameworks. The positive associations between vulnerability estimates and demographic decline indicate that large-scale assessments can provide useful information for evaluating risk and prioritizing conservation action where direct demographic data are limited.

Introduction

Human activities are reshaping the Earth at an unprecedented rate, with profound consequences for biodiversity across taxonomic groups (Ceballos et al., 2015; Díaz et al., 2019). Climate change has emerged as a major driver of these transformations, interacting with land-use change and other anthropogenic pressures to alter species distributions and population dynamics (Urban, 2015). As climate impacts intensify, conservation agencies increasingly rely on climate vulnerability assessments to identify species at risk and prioritize adaptation, monitoring, and recovery actions (IPBES, 2019).

The IUCN Red List Threats Classification Scheme (IUCN–CMP 2022) includes climate change as a threat category, but it is often assigned based on expected impacts within a defined future time window (e.g., three generations or 10 years; Trull et al., 2018), rather than on observed demographic decline. Consequently, conservation planning often depends on vulnerability assessments that are intended to predict future risk but are rarely evaluated against demographic data measuring population change. As a result, climate vulnerability assessments frequently reflect anticipated future risk, raising a fundamental question: do current vulnerability frameworks reliably identify species of conservation concern, or do they primarily capture longer-term risk that is not yet reflected in demographic trends?

Climate change vulnerability assessments (CCVAs) are increasingly used to identify species of conservation concern and guide adaptation planning, yet they rely on different assumptions and data requirements to quantify vulnerability, spanning correlative, mechanistic, and trait-based approaches (Pacifici et al., 2015; Willis et al., 2015; Wheatley et al., 2017; IPBES 2019). Trait-based vulnerability indices are among the most widely applied approaches because they can be implemented across large numbers of species using readily available ecological and life-history information (Foden et al., 2013; Wheatley et al., 2017; Richards et al., 2021). These frameworks typically combine traits related to sensitivity and adaptive capacity into composite vulnerability scores. Other approaches rely on quantitative estimates of exposure, most commonly using species distribution models (SDMs) that project future changes in climatic suitability and habitat availability (Wheatley et al., 2017; Bateman et al., 2020). Hybrid approaches combine projected environmental change with species traits to capture multiple dimensions of vulnerability (Wheatley et al., 2017).

Although these approaches share the goal of identifying species most vulnerable to climate change, they may produce different assessments of conservation risk and therefore different conservation priorities. Trait-based frameworks often rely on predefined assumptions about the direction and relative contribution of vulnerability components, whereas model-based approaches estimate those relationships directly from available data (Foden et al., 2013; Wheatley et al., 2017). Model-based approaches may therefore provide more flexible estimates of risk, but trait-based indices remain widely used because they are comparatively simple, transparent, and applicable even when extensive demographic or environmental data are unavailable. Understanding whether these alternative approaches identify the same species as

vulnerable is therefore important for evaluating the robustness of conservation prioritization decisions.

Despite their widespread use, opportunities to evaluate vulnerability assessments against demographic data remain rare (Wheatley et al., 2017). Long-term monitoring programs have documented widespread declines across North American bird populations (Rosenberg et al., 2019), creating a rare opportunity to assess whether climate vulnerability metrics identify species already exhibiting demographic signals consistent with elevated conservation risk. It therefore remains unclear whether commonly used vulnerability assessments identify the same species as vulnerable, whether they lead to similar conservation priorities, and whether their predictions align with observed population declines.

Here, we evaluate whether climate vulnerability assessments identify species exhibiting evidence of demographic decline. Breeding birds in Canada provide a useful test system because extensive population monitoring data allow vulnerability assessments to be evaluated against observed demographic change. Global assessments indicate that 24-50% of bird species may be vulnerable to climate change (Foden et al., 2013), and many are projected to experience range contractions under future scenarios (Jetz et al., 2007). Canada is particularly relevant for evaluating climate vulnerability because northern regions are warming at more than twice the global average, with Arctic systems experiencing even faster temperature increases (Bush & Lemmen, 2019). Birds breeding at high latitudes may therefore be disproportionately exposed to climatic shifts that alter habitat availability, disrupt migration timing and trophic synchrony, and ultimately affect population persistence (Smith et al., 2020).

We compared two integrated climate vulnerability frameworks that combine the same underlying variables in different ways, contrasting a fixed-weight index with a statistical model. First, we

calculated a Trait-based Vulnerability Index (TVI) adapted from Bateman et al. (2020), which combines exposure, sensitivity, and adaptive capacity into a composite score. Exposure was quantified using SDM-derived projected habitat loss and non-climate IUCN threats, whereas sensitivity and adaptive capacity were represented by species traits. Second, we developed a Climate Vulnerability Model (CVM) that used the same predictors to estimate the probability that a species is listed by the IUCN as threatened by climate change. We then tested whether vulnerability estimates from the TVI and CVM corresponded to measures of long-term population change in North American birds (Rosenberg et al., 2019). Specifically, we asked whether alternative vulnerability assessments identify the same species as vulnerable, whether vulnerability estimates are associated with evidence of demographic decline, and which components of vulnerability contribute most strongly to those relationships.

If climate vulnerability assessments provide useful information for conservation prioritization, species identified as highly vulnerable should be more likely to exhibit evidence of demographic decline. However, because different assessments emphasize different dimensions of risk, we expected them to differ in the species identified as vulnerable. We further hypothesized that exposure-based metrics would show the strongest association with observed population decline. Specifically, we expected cumulative threat burden and SDM-derived projected habitat loss to be positively associated with decline, reflecting growing evidence that climate-driven changes in environmental suitability are already contributing to population reductions in birds and other taxa (Stephens et al., 2016; Howard et al., 2020; Urban, 2015). By contrast, we expected intrinsic sensitivity and adaptive-capacity traits to show weaker direct associations with contemporary declines because their effects are likely to be context dependent and expressed over longer time scales.

Methods

Study system and vulnerability data

We evaluated climate vulnerability assessments for 247 bird species breeding in Canada, a region experiencing rapid climatic change and one of the few systems with sufficient demographic data to evaluate climate vulnerability assessments (Rosenberg et al., 2019; Leroy et al., 2026). Species were included when trait, climate exposure, IUCN threat, and long-term demographic data were available.

Vulnerability was characterized using three commonly applied dimensions: exposure, sensitivity, and adaptive capacity (Foden et al. 2013; 2017). Exposure included SDM-derived projected habitat loss and the number of non-climate IUCN threats. Sensitivity was represented by generation length, foraging breadth, and behavioural innovation, whereas adaptive capacity included migration index, habitat breadth, and clutch size. IUCN climate-change threat listings were used as an expert-based indicator of climate vulnerability. Because demographic estimates were available at the continental scale, we used IUCN climate-change threat listings rather than Canada-specific COSEWIC assessments. All variables were standardized prior to analysis and oriented such that higher values represented greater vulnerability. Detailed variable descriptions, data sources, and trait classifications are provided in Supplementary Methods (Table S1).

Climate exposure

Climate exposure was estimated as projected habitat loss derived from ensemble species distribution models (SDMs). Ensemble predictions were generated using Generalized Additive

Models, Boosted Regression Trees, and Maximum Entropy models fit with occurrence records and contemporary and future climate predictors. For each species, projected habitat loss was quantified as the reduction in climatically suitable habitat between current and future conditions and used as the exposure component of vulnerability. Detailed SDM procedures, validation, predictor selection, and model settings are provided in Supplementary Methods S2.

Alternative vulnerability assessments

Trait-based Vulnerability Index (TVI)

We constructed a Trait-based Vulnerability Index (TVI) by combining exposure, sensitivity, and adaptive-capacity variables into a single additive score (Fig. 1). The TVI represents a commonly used climate-vulnerability assessment approach in which vulnerability components are aggregated using predefined weighting and directional assumptions. Consequently, the relative contribution of each variable is specified a priori rather than estimated from empirical data.

Climate Vulnerability Model (CVM)

We developed a Climate Vulnerability Model (CVM) using Bayesian phylogenetic models with IUCN climate-change threat listing as the response variable (Fig. 1). In contrast to the TVI, the CVM retained exposure, sensitivity, and adaptive-capacity variables as separate predictors, allowing their relative contributions to climate vulnerability to be estimated directly from the data. To evaluate which dimensions of vulnerability contributed most strongly to climate-risk assessments, we fitted exposure-only, trait-only, and combined models, as well as models in which predictors were aggregated into a TVI-style composite index. Model performance was

evaluated using leave-one-out cross-validation (LOO). Full model specifications, phylogenetic methods, priors, and convergence diagnostics are provided in Supplementary Methods.

Demographic decline data

We used long-term species-level abundance estimates from Rosenberg et al. (2019), derived from multiple standardized monitoring programs across North America. Species were classified as declining or non-declining based on changes in abundance between 1970 and 2017. This demographic dataset was used to evaluate whether climate vulnerability assessments identified species already exhibiting population decline. Of the 247 species with vulnerability estimates, 236 had sufficient demographic data (non-missing population estimates for both 1970 and 2017) and were retained for this analysis.

Evaluating agreement among vulnerability assessments

To determine whether alternative vulnerability assessments identified similar conservation priorities, we compared vulnerability estimates from the TVI and CVM. Agreement between frameworks was evaluated by comparing species rankings and by quantifying overlap among highly vulnerable species using a prevalence-matched threshold based on the proportion of species listed by IUCN as climate-threatened. To assess whether aggregating vulnerability components altered inference, we also compared model formulations that retained vulnerability components as separate predictors with formulations based on a TVI-style composite index.

Evaluating vulnerability assessments against demographic decline

Do vulnerability assessments identify species experiencing demographic decline?

We tested whether vulnerability estimates from the TVI and CVM were associated with observed demographic decline by relating vulnerability estimates to a binary indicator of decline (declining vs. non-declining species). Bayesian logistic regression models were used to estimate whether species identified as highly vulnerable were more likely to exhibit population declines. Model performance was evaluated using leave-one-out cross-validation.

Which dimensions of vulnerability are associated with demographic decline?

To identify which dimensions of vulnerability were most strongly associated with demographic change, we modelled population decline as a function of exposure, sensitivity, and adaptive-capacity variables using Bayesian phylogenetic regression models. This analysis allowed us to evaluate the relative contributions of projected habitat loss, threat burden, and species traits without aggregating predictors into a composite vulnerability score.

Results

Comparing climate vulnerability assessments

Species vulnerability estimates from the TVI and CVM were positively associated, but agreement between frameworks was moderate (Spearman's $\rho = 0.24$, $P < 0.001$; Fig. 2). Overlap among highly vulnerable species was 0.356 (Jaccard similarity), with 32 of the 50 species classified as highly vulnerable by the CVM also classified as highly vulnerable by the TVI (Fig. 2). The distribution of vulnerability scores also differed in shape between frameworks, with

most species falling in the Moderate category under TVI (53% of species) but in the Low category under CVM (62.8% of species; Figure S3). Across model formulations, models retaining exposure, sensitivity, and adaptive-capacity variables as separate predictors had higher expected log predictive density (ELPD) values than formulations based on the composite TVI score (Table S1).

Drivers of climate vulnerability

Across candidate CVM formulations, models including exposure variables had the highest support (Table S2.1). The model including projected habitat loss, non-climate threat burden, and migration index achieved the highest ELPD, although differences among exposure-based models were small (ΔELPD ≤ 2.7). Trait-only models had substantially lower ELPD values (ΔELPD ≈ -42), and models based solely on the composite TVI score had the lowest support (ΔELPD ≈ -52). Coefficient estimates from the full model showed positive associations between projected habitat loss, non-climate threat burden, and the probability of climate-change listing (Fig. 3A). Migration index also showed a positive association with climate-change listing. Other sensitivity and adaptive-capacity variables had smaller coefficient estimates, with credible intervals overlapping zero in several cases (Fig. 3A). Predictive performance also varied by biome: CVM predictions of climate-change listing status were more accurate than TVI predictions in most biomes, particularly Arctic Tundra and coastal systems, whereas TVI performed comparably to or better than CVM for grassland-associated species (Figure S5).

Vulnerability components associated with demographic decline

Patterns were similar in models of population decline (Table S2.1). The model containing projected habitat loss and non-climate threat burden had the highest support (ΔELPD = 0). Adding sensitivity or adaptive-capacity variables resulted in small differences in predictive performance (ΔELPD ≥ -1.0), whereas trait-only models had lower support (ΔELPD ≈ -17 to -26). Projected habitat loss and non-climate threat burden had positive associations with the probability of population decline (Fig. 3B). Effect sizes for most sensitivity and adaptive-capacity variables were smaller, with broader credible intervals. Model outputs are presented as marginal effects on the probability scale to facilitate comparison among predictors (Fig. 3A–B).

Climate vulnerability and population decline

Predicted climate vulnerability from the best-supported CVM was positively associated with observed population decline (Fig. 4). Species with higher predicted probabilities of climate-change listing were more likely to have declined between 1970 and 2017 (β = 2.18, 95% CrI [0.98, 3.44]). When phylogenetic covariance was excluded, the estimated association was similar in magnitude (β = 1.84, 95% CrI [0.85, 2.85]).

Discussion

Climate vulnerability assessments are increasingly used to prioritize conservation action, yet their predictive validity remains largely untested because demographic data are unavailable for most species (Wheatley et al., 2017, Lu & Jetz, 2023). Using breeding birds as a system with extensive demographic monitoring data, we compared alternative climate vulnerability assessments and evaluated their relationship with observed population decline. We found that: 1)

alternative assessments identified overlapping but distinct sets of vulnerable species, 2) exposure variables consistently showed stronger associations with vulnerability than intrinsic traits, and 3) modelled climate vulnerability was positively associated with long-term population decline.

Alternative climate vulnerability assessments identify different species

Despite being constructed from the same underlying vulnerability variables, TVI and CVM showed only moderate agreement and identified different sets of highly vulnerable species. This pattern is consistent with previous comparisons among vulnerability frameworks (Wheatley et al., 2017), but demonstrates that disagreement can arise even when assessments are based on the same information. The primary difference between the two approaches lies in how vulnerability is quantified. TVI combines vulnerability components using fixed directional assumptions and equal weighting, whereas CVM estimates the relative contribution of each predictor directly from the data.

These differences have practical implications because vulnerability assessments are increasingly used to support conservation planning and adaptation strategies. The moderate overlap between TVI and CVM indicates that methodological assumptions can influence vulnerability estimates independently of the variables used to generate them. Importantly, this result does not imply that trait-based assessments are incorrect. Trait-based indices remain attractive because they can be applied across large numbers of species with relatively limited data requirements. However, our results suggest that alternative approaches can produce different vulnerability estimates and identify different sets of species as highly vulnerable. This pattern echoes a broader empirical

trend: validation studies comparing vulnerability-assessment approaches against observed population and distribution changes have generally found greater support for trend- or exposure-based methods than for purely trait-based assessments (Wheatley et al., 2017; Foden et al., 2019a). This divergence was not uniform across taxa: seabirds showed the highest vulnerability of any guild under TVI (mean ≈ 0.86) but comparatively low and more uncertain vulnerability under CVM (mean ≈ 0.59; Figure S4), indicating that the two frameworks can disagree most strongly for particular groups of species.

Exposure variables dominate climate-vulnerability assessments

Across climate-vulnerability models, projected habitat loss and non-climate threat burden showed stronger associations with climate vulnerability than sensitivity or adaptive-capacity traits. Exposure-inclusive models consistently outperformed trait-only formulations, and projected habitat loss was among the strongest predictors of climate-change threat listing.

These results are broadly consistent with existing climate-vulnerability frameworks, which recognize exposure, sensitivity, and adaptive capacity as complementary dimensions of vulnerability (Wheatley et al., 2017). However, exposure variables provided the strongest detectable signal in our analyses. One possible explanation is that exposure is often quantified directly through projected environmental change, whereas sensitivity and adaptive capacity are typically represented using indirect trait-based proxies. As a consequence, exposure may be easier to detect statistically because it is both biologically important and more directly measured. The relatively weak trait effects do not imply that sensitivity and adaptive capacity are unimportant. Many documented trait-risk relationships are threat-specific and emerge only under

particular environmental conditions. Traits may therefore be most informative when linked to specific mechanisms of decline rather than assessed as general predictors across multiple interacting drivers.

Migration: sensitivity rather than adaptive capacity component

Migration was the only trait consistently associated with climate-change threat listing. Although migration is commonly interpreted as a component of adaptive capacity, migratory species experience environmental conditions across breeding, stopover, and wintering areas and may therefore be exposed to a broader range of climatic and anthropogenic pressures (Johnson et al., 2006; Thaxter et al., 2014; Jiguet et al., 2019). This is consistent with broader evidence that migratory status elevates conservation risk: long-distance migrants have shown steeper population declines than resident or short-distance migrant species across North American and global bird assemblages (Rosenberg et al., 2019; Lees et al., 2022; Serrano et al. 2025), and unsustainable harvest along migratory flyways can drive population declines independent of conditions on the breeding grounds (Jiguet et al., 2019). Because migratory status integrates exposure to multiple, geographically distinct threats rather than reflecting a single fixed trait value, it may be better understood as a proxy for cumulative exposure across the annual cycle than as a conventional sensitivity or adaptive-capacity trait.

Exposure variables are also associated with demographic decline

A key challenge for climate-vulnerability assessments is determining whether estimated vulnerability corresponds to realized biological change. Despite being designed primarily to

characterize climate-related risk, vulnerability assessments may capture environmental pressures that are already influencing population trajectories. In out study, projected habitat loss and non-climate threat burden were the strongest predictors of observed population decline, whereas sensitivity and adaptive-capacity traits provided comparatively little additional predictive information.

The correspondence is notable because climate-vulnerability assessments are designed to characterize potential risk, whereas population trends reflect realized demographic change accumulated over decades. The association of exposure variables with both IUCN climate-change listings and population decline suggests that projected habitat loss and cumulative threats capture information relevant to contemporary population trajectories. However, these associations should not be interpreted as evidence of direct causal effects of climate change. Population trends emerge from multiple interacting drivers, including climate change, land-use change, and other anthropogenic pressures (Gonzalez et al., 2023; Serrano et al., 2025). Exposure metrics may therefore be particularly informative because they integrate broad patterns of environmental pressure, rather than isolating individual causal mechanisms.

Climate vulnerability and past population declines are linked

Climate-vulnerability assessments are often one of the few approaches available for identifying species at risk when detailed demographic data are lacking, relying instead on species-level information derived from empirical measurements or expert knowledge. Importantly, these assessments are intended to be anticipatory, identifying risk before the consequences of climate exposure are fully reflected in population trajectories. Demographic responses to environmental

change may occur with substantial lags, particularly in long-lived species, and these lags are likely to vary among taxa. Nevertheless, climate-related responses are already being observed in bird populations (Stephens et al., 2016; Howard et al., 2020), providing an opportunity to evaluate whether estimated vulnerability is beginning to be reflected in demographic change.

Species assigned higher modelled climate vulnerability were more likely to exhibit long-term population decline. This relationship provides a rare empirical evaluation of climate-vulnerability assessments using demographic data. Breeding birds provide one of the few systems where this comparison is possible because extensive population monitoring data can be used to evaluate whether vulnerability estimates correspond to realized demographic patterns. The positive association between modelled vulnerability and population decline suggests that vulnerability assessments capture biologically meaningful variation associated with demographic risk.

At the same time, the relationship between vulnerability and decline was imperfect. Vulnerability assessments are designed to estimate risk under ongoing and future environmental change, whereas observed population trajectories reflect the cumulative effects of multiple drivers operating over time and may not yet capture the full demographic consequences of recent climate exposure. Consequently, some divergence between vulnerability estimates and demographic outcomes is expected. Such divergence may reflect both time lags in demographic responses and the multiple interacting pressures affecting populations, rather than necessarily indicating that vulnerability estimates poorly characterize future risk.

Implications for conservation prioritization

Our results highlight the importance of distinguishing between vulnerability assessment and vulnerability validation. Vulnerability assessments are increasingly used to guide conservation planning and adaptation strategies, yet empirical evaluations remain uncommon. The moderate agreement between TVI and CVM indicates that framework choice can influence vulnerability estimates, while the stronger associations observed for exposure variables suggest that projected environmental change contains substantial information about near-term conservation risk.

Our findings do not suggest that traits should be excluded from vulnerability assessments. Rather, they indicate that exposure variables provided the strongest detectable signal of vulnerability at the temporal and spatial scales considered here. Integrating exposure estimates, trait information, and demographic trajectories may ultimately provide a more complete representation of climate vulnerability than any single component alone. As climate-vulnerability assessments become increasingly incorporated into conservation prioritization and adaptation planning, opportunities to evaluate assessment outcomes against demographic evidence will remain critical. Improving the empirical basis of vulnerability assessments will help ensure that conservation decisions are informed by the strongest available evidence under ongoing environmental change.

Recommendations

Overall, our findings suggest that climate-vulnerability assessments can provide useful information for conservation decision-making, but their value depends on the framework, information, and context used to characterize vulnerability. We therefore recommend that

multiple frameworks are evaluated and compared before treating a single framework as authoritative. Where possible, practitioners should cross-check rankings across multiple frameworks and flag species identified as vulnerable by only one approach for closer review before prioritizing or deprioritizing conservation actions.

Where appropriate data are available, exposure metrics should anchor prioritization. These could be projected exposure derived from species distribution models, threat assessments, or other spatially explicit information can complement trait-based indicators, whereas trait-based approaches remain particularly useful for data-poor taxa or situations where measures of exposure are unavailable. Particular attention should be given to species exposed to multiple threats or substantial habitat-related pressures, because cumulative pressures may increase vulnerability beyond that indicated by individual threats considered in isolation.

Migratory species, however, should be treated as a particularly more at-risk group regardless of exposure, and may need explicit consideration beyond migration being considered a component of sensitivity or adaptive capacity alone. For these species, assessments should ideally consider vulnerability across the full annual cycle, including exposure during breeding, migrations and nonbreeding periods.

The choice of vulnerability framework should also reflect the taxonomic, ecological, and regional context in which it will be applied. Where independent demographic or ecological information is available, it should be used to evaluate whether vulnerability assessments capture meaningful patterns of climate and extinction risk in the species and regiones of interest.

Finally, continued investment in long-term demographic monitoring is essential for improving and evaluating vulnerability assessments. Vulnerability scores should be considered one line of

evidence rather than direct rankings for conservation action and integrated with population trends, conservation status, documented threats, expert knowledge, and the feasibility of conservation interventions. In this way, vulnerability assessments can help identify species requiring closer attention while informing, rather than determining, conservation priorities.

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Figures

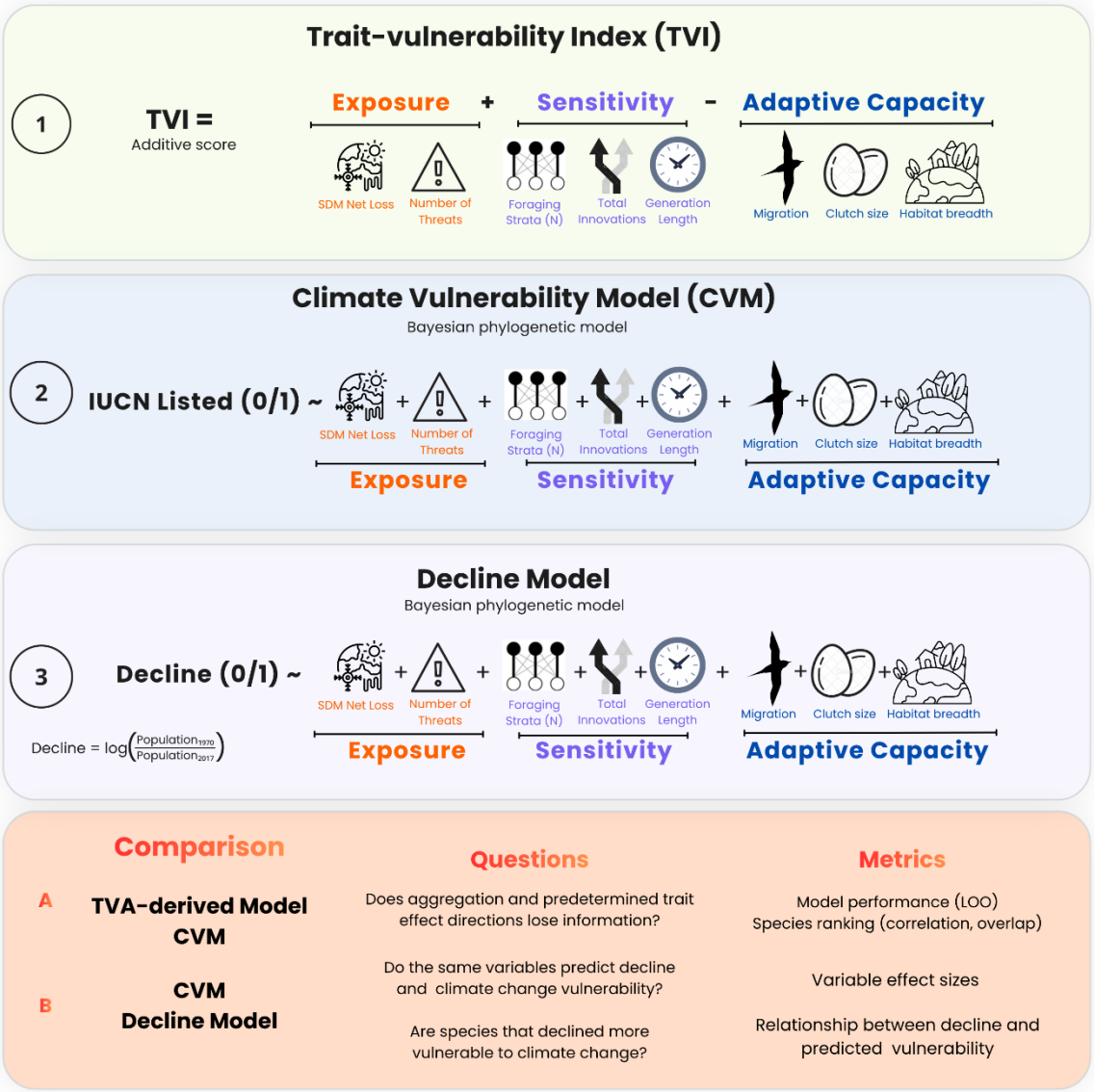

Figure 1. Conceptual framework comparing trait-based (TVI) and model-based (CVM) climate vulnerability and their relationship to demographic decline. TVI aggregates exposure, sensitivity, and adaptive capacity into a composite index, whereas CVM estimates the independent effects of the same predictors within a phylogenetic model. Frameworks were compared using climate-change listing as a common response, and validated by testing whether predictors and model-based vulnerability explain observed population decline.

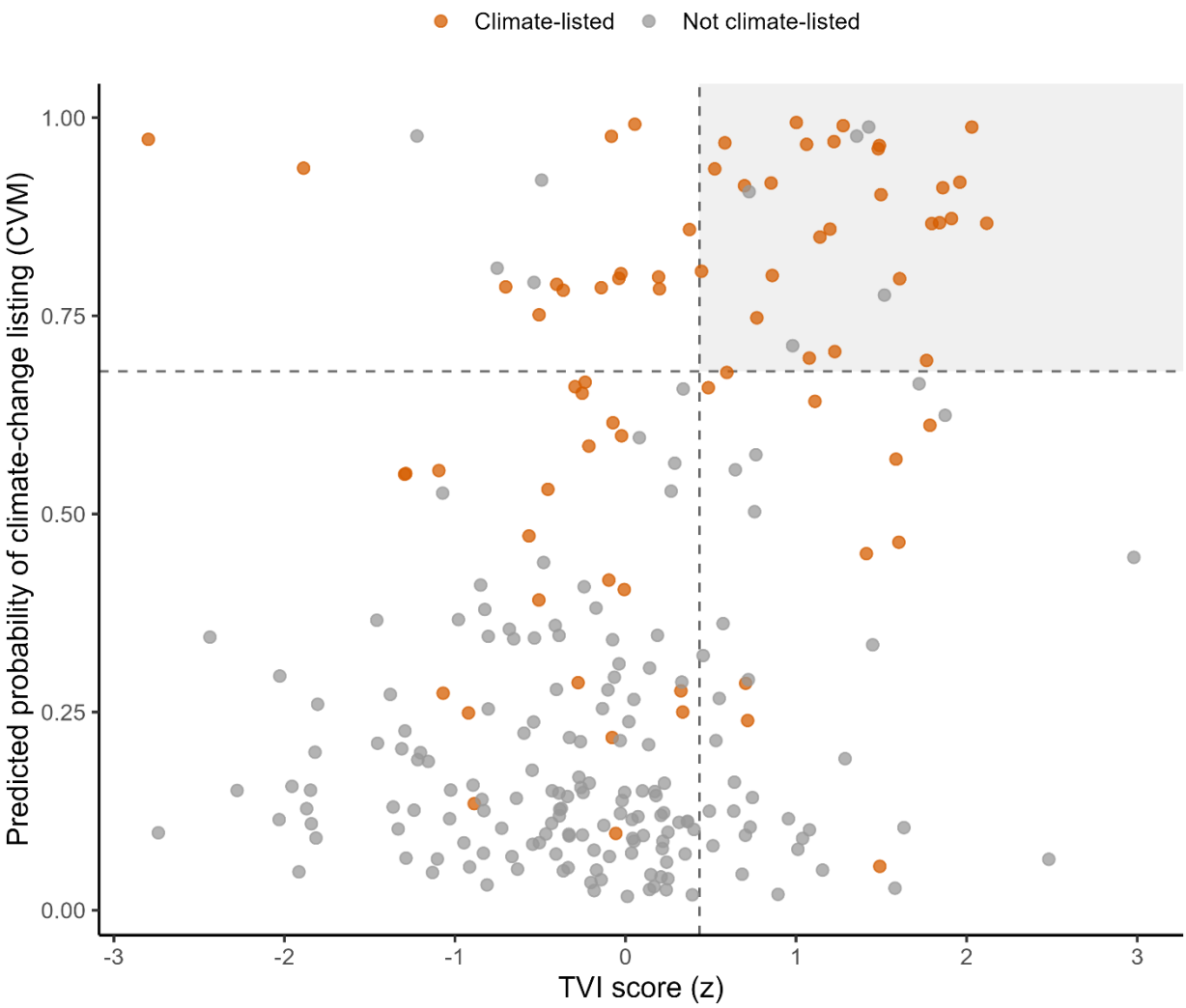

Figure 2. Agreement between trait-based and model-based vulnerability. Relationship between trait-based vulnerability (TVI) and model-based climate-change vulnerability (CVM) for Canadian breeding birds. The y-axis shows the predicted probability of climate-change listing from the full phylogenetic CVM model, and the x-axis shows standardized TVI scores. Each point represents a species and is colored according to IUCN climate-change threat listing status. Dashed lines indicate thresholds used to define highly vulnerable species (the mean predicted score among species already listed by IUCN as climate-threatened, for each framework), and the shaded region highlights species classified as highly vulnerable by both frameworks. Overall concordance across species was moderate (Spearman's $\rho = 0.24$, $P < 0.001$), whereas agreement among highly vulnerable species was more limited (32 of 50 species; Jaccard = 0.356).

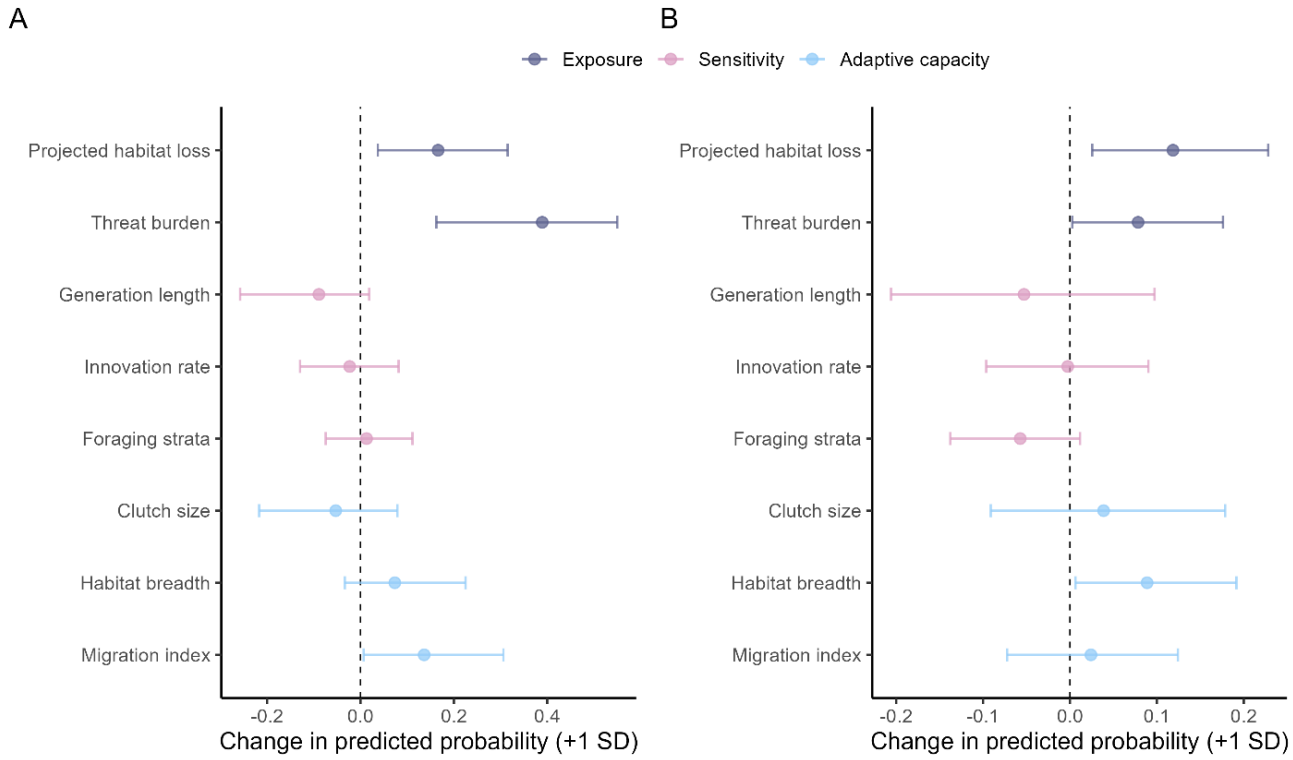

Figure 3. Standardized marginal effects of vulnerability components on climate-change listing and observed decline risk. Effect sizes represent the change in predicted probability associated with a one standard deviation increase in each predictor, holding all other variables at their means. Panels show (A) the probability of IUCN climate-change threat listing and (B) the probability of observed population decline (pop2017 < pop1970). Points indicate posterior means and bars show 95% credible intervals. Colors denote vulnerability components: exposure (projected habitat loss and non-climate threat burden; dark blue), sensitivity (pink), and adaptive capacity (light blue). In panel (A), probabilities are derived from the full phylogenetic CVM model, where climate-change listing is defined based on IUCN threat classification. In panel (B), probabilities are derived from a model of demographic change using a binary decline response. This binary formulation was used to express marginal effects on a comparable probability scale; continuous decline magnitude was modeled separately. Across both panels, exposure variables show the strongest positive effects, whereas intrinsic trait effects are comparatively weak. This probability-based representation was used to facilitate direct comparison of effect sizes across trait-based (TVI), model-based (CVM), and demographic (decline) frameworks, given that the underlying models differ in structure and response scale.

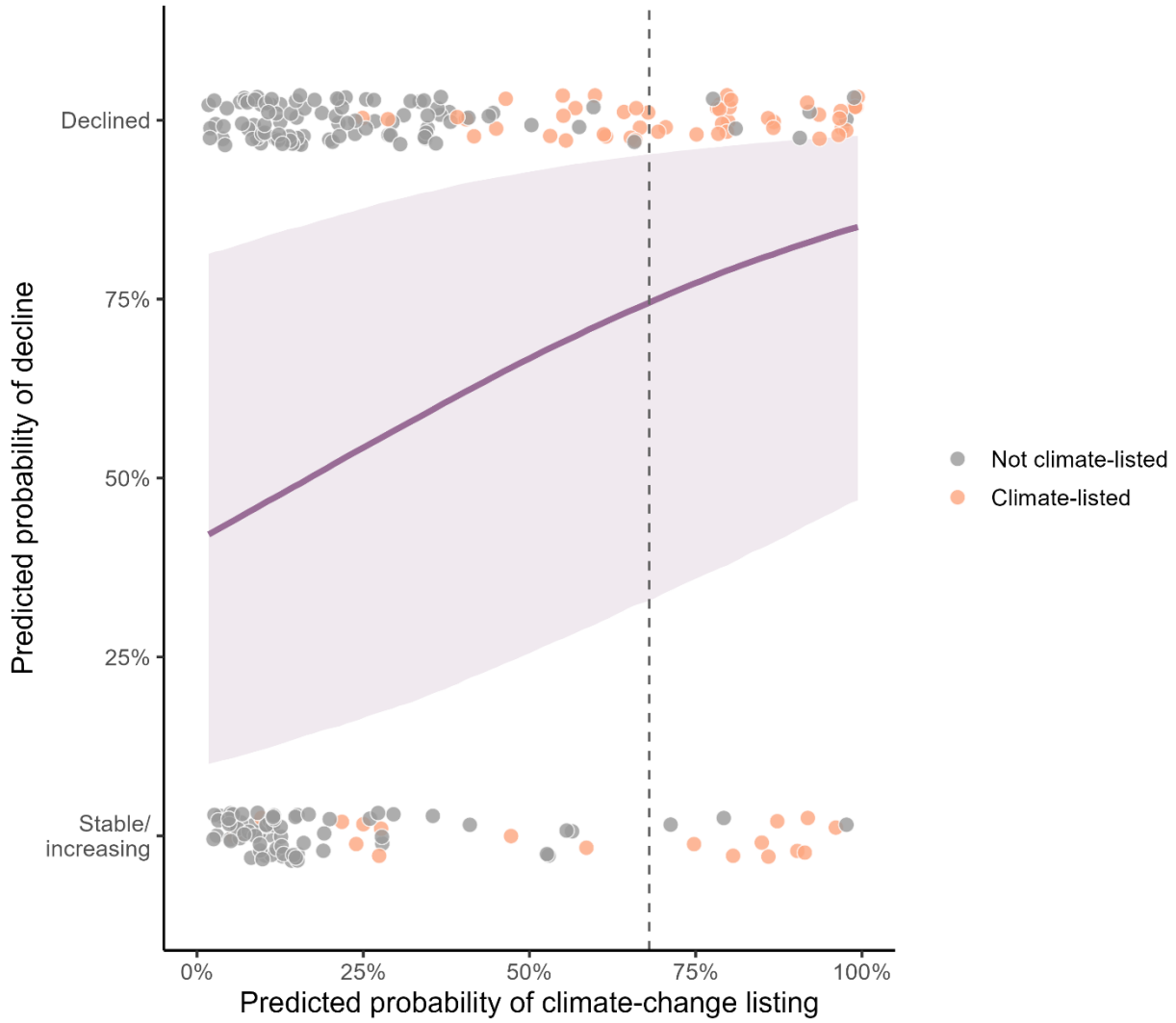

Figure 4. Relationship between the predicted probability of climate-change threat and the probability of observed population decline among Canadian breeding bird species (n=236), modeled from binary response (declined or not). Points represent binned empirical proportions of species that declined (1970–2017), with point size proportional to the number of species per bin. The solid line shows the posterior mean relationship from a Bayesian phylogenetic logistic regression (binary decline response), and the shaded region represents the 95% credible interval. Predicted climate vulnerability strongly increased the probability of decline (β = 2.18, 95% credible interval: 0.98–3.44, log-odds scale), corresponding to an approximately ninefold increase in the odds of decline across a one-unit increase in predicted vulnerability.

Supplementary materials

Supplementary methods

Vulnerability variables

Climate vulnerability was characterized using three commonly used dimensions: exposure, sensitivity, and adaptive capacity (Foden et al., 2013; Wheatley et al., 2017; Bateman et al., 2020). Variables were assigned to vulnerability dimensions to facilitate comparison with previous climate-vulnerability frameworks:

Exposure was quantified using projected habitat loss derived from species distribution models (SDMs) and the number of non-climate threats listed in the IUCN Red List. Projected habitat loss was used to represent the potential effects of future climatic change on habitat suitability, whereas non-climate threat burden was included to account for interacting pressures that may amplify climate-related risk.

Sensitivity was represented by generation length, foraging breadth, and behavioural innovation. Generation length was classified as a sensitivity trait because species with longer generation times may respond more slowly to rapid environmental change through demographic or evolutionary processes. Foraging breadth and behavioural innovation were included because they may influence species persistence under changing environmental conditions.

Adaptive capacity was represented by migration index, habitat breadth, and clutch size. These variables are commonly interpreted as indicators of dispersal ability, ecological flexibility, and demographic resilience in climate-vulnerability assessments. Although some traits could plausibly influence multiple dimensions of vulnerability, classifications were kept consistent across analyses and with previous frameworks. All predictor variables were standardized to mean

zero and unit variance prior to analysis. Trait directions were aligned such that higher values consistently reflected greater vulnerability.

Table S1: Variables and traits included in SDMs, TVI, and models.

SDM Variables	Predictor Variables
Climatic[1]	Mean Annual Precipitation (mm) Degree-days below 0°C Precipitation as snow (mm) Hargreave's climatic moisture index Degree-days above 18°C
Topographic	Topographic wetness index Topographic ruggedness index Land cover
TVI Components	**Traits**
Sensitivity	Persistence Ability: Number of Foraging Strata Total Innovations Generation Length
Adaptive Capacity	Dispersal Ability: Number of Habitats[3] Clutch Size Migration Index[4]
Exposure	Number of Threats[5] Net Loss in Suitable Habitat[2]

[1] AdaptWest Project 2022; [2] SDM predictions; [3] Number of habitats listed by IUCN; [4] Index is a combination of migration distance (long or short) and status (obligatory or facultative), [5] Number of threats listed by IUCN

Species distribution models and climate exposure

Climate exposure was estimated from ensemble species distribution models (SDMs). Bird occurrence records were obtained from GBIF for species breeding in Canada and the United States. Records were filtered to retain breeding-season observations only and observations collected from 2000 onward to reduce spatial uncertainty and mismatches with contemporary climate conditions. Occurrences were restricted to breeding distributions using IUCN breeding polygons where available and expert-derived range limits otherwise.

Environmental predictors included climatic and habitat variables previously shown to perform well for modelling breeding bird distributions. These included mean annual precipitation, degree-days below 0°C, precipitation as snow, Hargreaves climatic moisture index, and land-cover variables (Table S2.1). Climate predictors were obtained from the AdaptWest dataset. Current climatic conditions represented the period 1991-2020, whereas future conditions were derived from projections for 2080 under the RCP 8.5 emissions scenario.

For each species, we fitted two modelling algorithms: Generalized Additive Models (GAMs) and Boosted Regression Trees (BRTs), implemented using the *mgcv*, *gbm*, and *dismo* packages (Wood, 2011; Ridgeway, 2024; Hijmans et al., 2017). Models were trained using observations from both Canada and the United States to capture the full environmental gradient occupied by each species. Predictions were subsequently generated across Canada at a 5-km grid resolution. Boosted Regression Trees were fitted using a Bernoulli distribution, tree complexity of four, learning rate of 0.008, and bagging fraction of 0.5.

To account for environmental and spatial structure in occurrence data, we implemented two complementary five-fold cross-validation procedures using the *blockCV* package (Valavi et al., 2018). Environmental blocking grouped observations according to similarity in environmental

conditions, whereas spatial blocking partitioned observations latitudinally across North America. Validation was conducted within species-specific breeding ranges defined as IUCN breeding distributions plus a 500-km buffer. Model performance was evaluated using the Area Under the Receiver Operating Characteristic Curve (AUC) and the Area Under the Precision-Recall Curve (AUPRC). Summary validation statistics are shown in Figure S2.1. Ensemble predictions were generated by averaging the predictions from both modelling algorithms. Climate exposure was quantified as projected habitat loss, calculated from the difference between current and future suitability predictions across Canada. Species experiencing greater reductions in climatically suitable habitat were considered more exposed to climate change. Projected habitat loss was subsequently used as the exposure component in all vulnerability analyses.

Climate vulnerability models

The Trait-based Vulnerability Index (TVI) was constructed by combining exposure, sensitivity, and adaptive-capacity variables into a single composite score. Vulnerability components were assigned equal weight and aggregated additively following approaches commonly used in climate-vulnerability assessments. Consequently, vulnerability was determined by predefined assumptions regarding the direction and contribution of individual variables rather than by empirical estimation.

The Climate Vulnerability Model (CVM) was fitted using Bayesian phylogenetic logistic regression implemented in the *brms* package (Bürkner, 2017). The response variable was IUCN climate-change threat listing, treated as a binary indicator of whether a species had been identified as threatened by climate change. Models used a Bernoulli likelihood with a logit link

function and were fitted with four chains of 4,000 iterations each. Sampler settings were adjusted through increased values of *adapt_delta* to ensure stable convergence.

Phylogenetic non-independence was accounted for by including a species-level random effect with covariance structure derived from the Hackett backbone phylogeny. Phylogenies were obtained from Jetz et al. (2012, 2014) and pruned to match the analysed species set using the *ape* and *phytools* packages (Paradis et al., 2004; Revell, 2024). Convergence was assessed through potential scale reduction factors ($\hat{R} < 1.01$), effective sample sizes, and visual inspection of trace plots (Vehtari et al., 2021). Model formulations included exposure-only models, trait-only models, combined exposure-and-trait models, and models in which predictors were aggregated into a TVI-style composite index.

Model comparison and validation

Predictive performance of alternative vulnerability models was evaluated using leave-one-out cross-validation (LOO) (Vehtari et al., 2017). Model support was assessed using expected log predictive density (ELPD), where larger values indicate better expected out-of-sample predictive performance. Differences in ELPD were interpreted relative to their associated standard errors. Complete model comparison results are presented in Table S2.1.

To evaluate whether vulnerability assessments identified species exhibiting demographic decline, vulnerability estimates were related to long-term population change derived from Rosenberg et al. (2019). Additional model formulations evaluated the association between individual vulnerability components and demographic decline. All Bayesian models used the same phylogenetic framework described above.

Table S2. Model comparison using leave-one-out cross-validation (LOO) for candidate Bayesian phylogenetic models predicting IUCN climate-change listing (CVM) and , and observed population decline. Models are ranked by expected log predictive density (elpd_loo). Higher values indicate better out-of-sample predictive performance. Delta elpd represents the difference in predictive performance relative to the best-supported model. Differences smaller than approximately twice the standard error indicate models with comparable support. P_loo denoted the effective number of parameters.TVI

Model	elpd_loo	se_elpd	p_loo	se_p_loo	looic	se_looic	delta_elpd	delta_looic
Climate vulnerability models (CVM) and Trait-based index (TVI) derived models								
m_cvm_exposure_mig	-87.34	10.38	16.74	2.66	174.67	20.77	0	0
m_exposure	-88.18	10.22	15.58	2.48	176.36	20.44	-0.84	1.69
m_exp_adap	-89.08	10.72	19.93	3.1	178.16	21.43	-1.74	3.49
m_traitPCA1	-89.36	10.43	16.99	2.66	178.73	20.86	-2.03	4.06
m_exp_sens	-89.95	11.08	19.68	3.11	179.9	22.17	-2.61	5.23
m_cvm_full	-90.03	11.48	24	3.73	180.05	22.95	-2.69	5.38
m_mig_net	-121.77	9.23	15.65	1.7	243.54	18.47	-34.44	68.87
m_cc_tvi_phylo	-123.21	9.29	17.51	1.99	246.43	18.57	-35.88	71.76
m_traits	-129.54	9.71	27.68	2.94	259.07	19.43	-42.2	84.4
m_cc_tvi_only	-139.43	7.84	2.28	0.34	278.85	15.68	-52.09	104.18
Decline models								
m_decl_exposure	-249.07	18.01	26.53	1.43	498.13	36.02	0	0
m_decl_exp_adap	-249.77	17.95	31.3	1.66	499.54	35.89	-0.7	1.41
m_decl_exp_sens	-250.11	17.98	27.62	1.49	500.23	35.96	-1.05	2.1
m_decl_full	-252.51	17.87	32.43	1.73	505.03	35.74	-3.45	6.9
m_decl_tvi_phylo	-266.31	17.51	21.51	1.22	532.61	35.03	-17.24	34.48
m_decl_null	-269.45	17.58	18.28	1.07	538.91	35.16	-20.39	40.78
m_decl_adap	-271.06	17.56	22.29	1.29	542.12	35.12	-21.99	43.99
m_decl_sens	-271.12	17.61	21.04	1.23	542.24	35.22	-22.05	44.11
m_decl_tvi_only	-275.02	17.79	4.29	0.54	550.05	35.58	-25.96	51.92

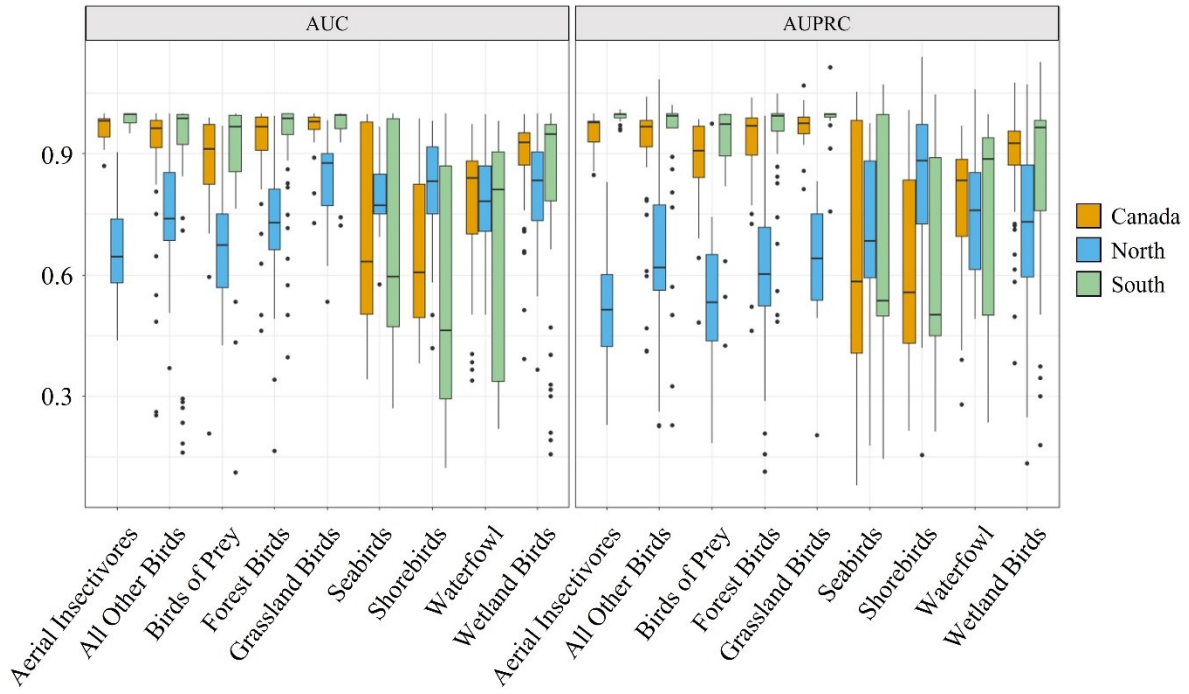

Figure S2. Species distribution model validation metrics (AUC and AUPRC) across three sets: all of Canada, Northern Canada (delineated by degree days below 0 greater than 1553), and Southern Canada (delineated by degree days below 0 less than or equal to 1553).

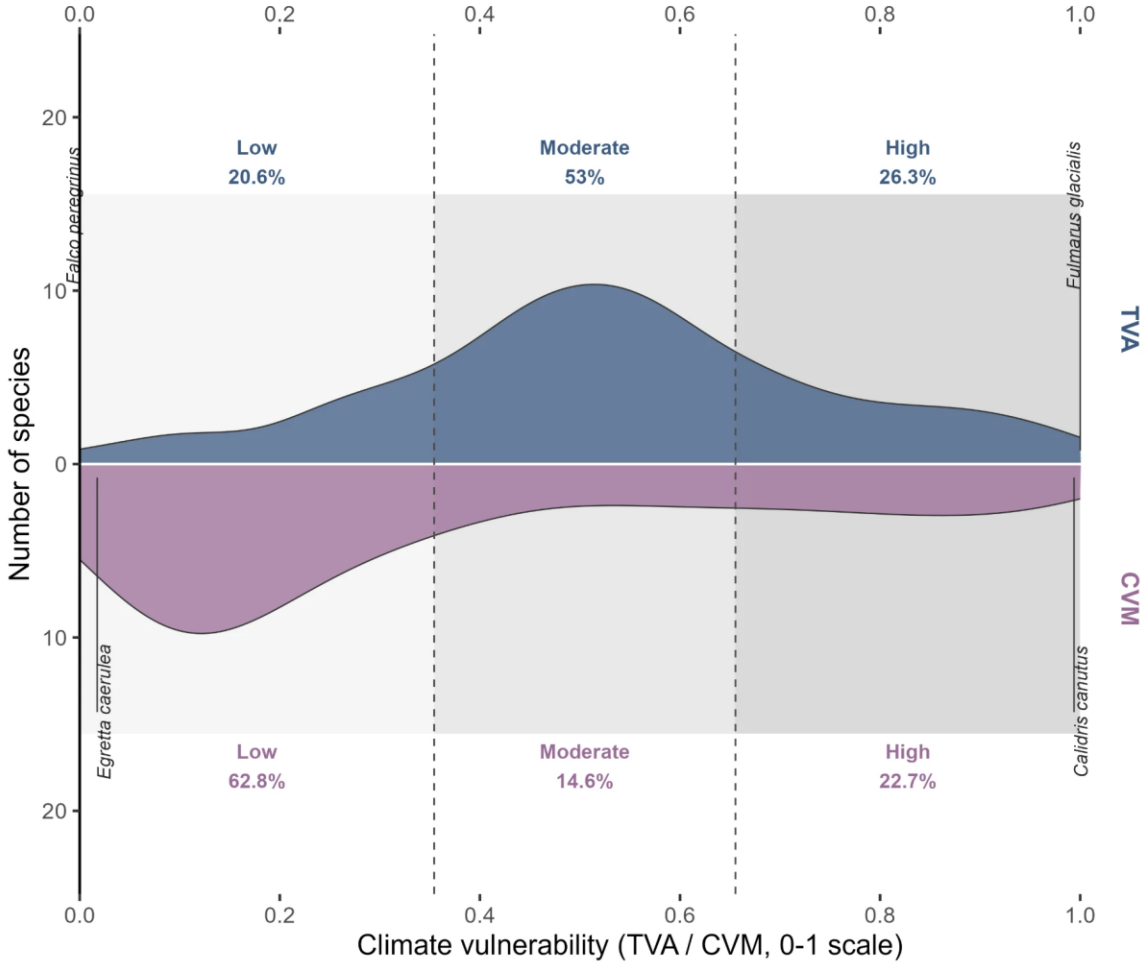

Figure S3. Distribution of predicted climate vulnerability scores under the TVI (top) and CVM (bottom) frameworks, rescaled to a common 0–1 scale using robust (1st–99th percentile) min–max scaling. Densities are shown as the number of species per 0.02-wide bin. Dashed vertical lines mark the shared Low/Moderate/High vulnerability thresholds (see Methods), with the percentage of species falling in each category shown above (TVI) and below (CVM) the axis. Labeled points indicate the species with the lowest and highest score under each framework.

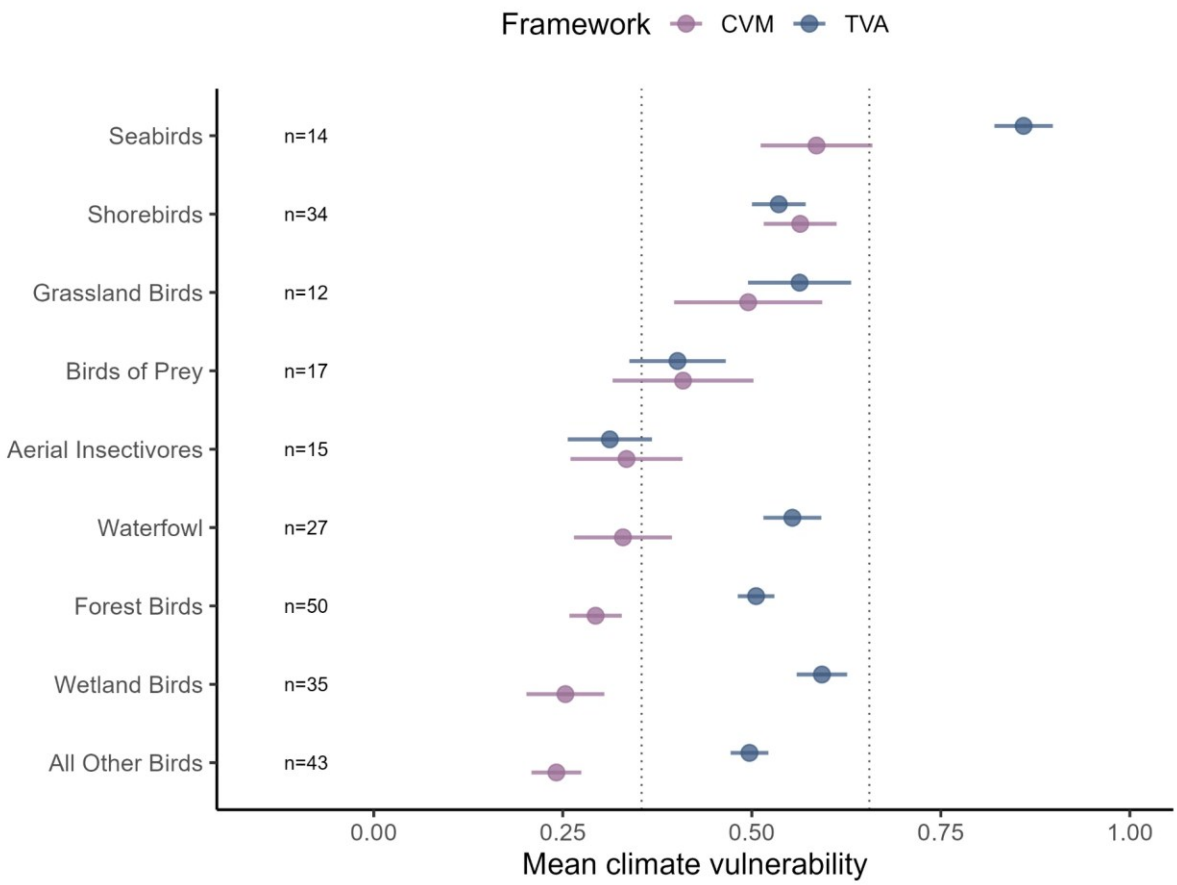

Figure S4. Mean predicted climate vulnerability (± 95% credible interval) under the TVI and CVM frameworks, grouped by avian guild. Sample sizes (n) indicate the number of species per guild.

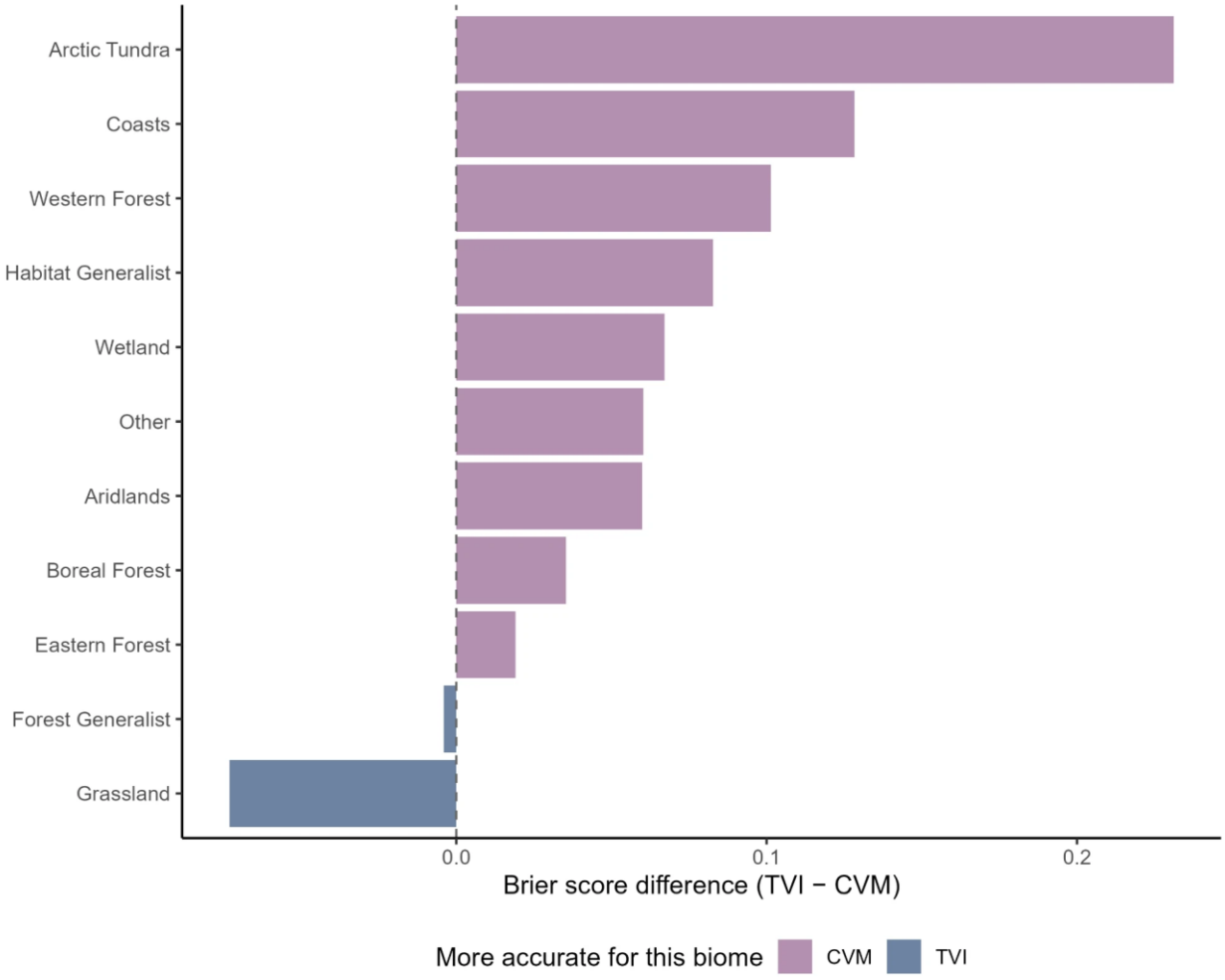

Figure S5. Difference in Brier score between the TVI and CVM frameworks (TVI − CVM) for predicting IUCN climate-change threat listing, grouped by biome. Positive values indicate biomes for which CVM predictions were more accurate; negative values indicate biomes for which TVI predictions were more accurate.