Unstructured community science data reveal constriction of breeding distribution for a common montane bird across the Fennoscandian peninsula

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Abstract

The threat of climate change is particularly acute for species in arctic and montane habitats, where changes are happening the most rapidly. Species are generally expected to shift their ranges northward and upslope in response to changing climates, but actual measured shifts in species distributions have been nuanced and large quantities of data are needed to accurately assess shifts. The growing availability of unstructured community science data is an appealing solution to the problem of characterizing changes in species distributions, but these data contain known biases that must be overcome to draw strong inference. Here, we leveraged opportunistic, unstructured community science data from across the Fennoscandian peninsula over the last 45 years to evaluate the hypothesis that the breeding distribution of a common and iconic montane bird, the bluethroat (*Luscinia svecica*), has shifted towards higher latitudes and elevations. We constructed non-detections of bluethroats using detections of 12 less notable 'background' avian species, which allowed us to analyze over 500,000 observations within a robust spatio-temporal occupancy modeling framework. We found that bluethroat occupancy has declined substantially over the past four decades across Fennoscandia. The largest absolute declines in occupancy probability took place in areas with higher occupancy in the early years of the study, but the largest relative changes in occupancy took place at low latitudes and low elevations at high latitudes. Our work demonstrates that even common and globally stable species are at risk of breeding habitat loss under the looming threat of climate change and that unstructured community science data, when used thoughtfully, can fill important knowledge gaps about species responses to global change.

1 Introduction

Climate change is influencing species distributions on a global scale (Parmesan and Yohe, 2003; Chen et al., 2011), and species adapted to northern climates are acutely affected because the Arctic is warming as much as four times faster than the rest of the globe (Stuecker et al., 2018; Rantanen et al., 2022). In general, species are expected to demonstrate latitudinal and elevational movements in which their range boundaries shift towards the poles and towards higher elevations to track their climatic niche (Thomas and Lennon, 1999; Chen et al., 2011; Walther, 2010; Hickling et al., 2006). In reality, though, observed distribution changes are nuanced. While many species ranges have shifted uphill or towards the poles, others have remained seemingly constant, and some have actually shifted downslope or towards the equator (Chen et al., 2011; Lenoir et al., 2010; Hickling et al., 2006). This variation in responses to climate change is hardly surprising given that species distributions are influenced by a wealth of interacting abiotic and biotic factors (Hughes, 2000; Hällfors et al., 2024; Archaux, 2004; Bateman et al., 2016; Tsiftsis et al., 2024), and geographic shifts in climate envelopes are only partly associated with latitude and elevation (Lenoir and Svenning, 2015; VanDerWal et al., 2013). Nevertheless, understanding how distributions are changing is an essential part of understanding and responding to threats to biodiversity posed by rapid changes in climatic conditions (Chen et al., 2011; Hovick et al., 2016). However, characterizing changes in species distributions over large geographic areas can be challenging, due to the need for large amounts of data over broad spatial and temporal scales.

The increasing quantity of community science data (also known as citizen science or participatory science data) and the expansive geographic ranges encompassed by these data make them an appealing solution to the problem of characterizing changes in species distributions (Theobald et al., 2015; Soroye et al., 2018). Community science data fall along a continuum between structured data, resulting from coordinated survey efforts where participants typically collect data following a standardized protocol designed to reduce various sources of bias and allow estimation of metrics of interest (Hochachka et al., 2012; Altwegg and Nichols, 2019), and opportunistic data, resulting from casual observations of species reported with varying amounts of associated metadata (Kamp et al., 2016). Structured data (e.g., resulting from population monitoring schemes) have led to many important insights (Lehikoinen et al., 2014; Rosenberg et al., 2019; Sauer et al., 2017), but can be time-consuming, difficult, and expensive to organize and collect, especially at large spatial scales. Indeed, opportunistic data are increasing the most rapidly in quantity and spatial coverage (Pocock et al., 2017), but these data present an array of challenges for drawing strong inference (Johnston et al., 2023) and may not match the power of structured data to characterize trends of interest (Kamp et al., 2016).

Opportunistic data can be unstructured or semi-structured. Semi-structured data are collected opportunistically, but also require observers to submit information about the observation process (e.g., checklists on eBird). Semi-structured data are increasingly used to draw strong inference about bird distributions and population trends (Johnston et al., 2025; Rosenberg et al., 2019). However, there is also a wealth of unstructured opportunistic data with little to no information about the observation process. These data are typically detection-only, meaning they include information about where species were observed but not where effort was expended and a particular species was not observed. These data also suffer from potential spatial and temporal bias, as well as bias resulting from observer behavior, such as a tendency to report exciting or notable species but not common or drab species (Johnston et al., 2023; van Strien et al., 2013). Overcoming some of these sources of bias could enhance our ability to draw inference from these large and readily-available unstructured participatory science datasets.

Here, we leverage opportunistic, unstructured participatory science data to understand whether the occupancy dynamics of a common montane bird, the bluethroat (*Luscinia sve-*

cica svecica), conform to expectations under climate change across the Fennoscandian peninsula. Specifically, we evaluate the hypothesis that the breeding distribution of the bluethroat has shifted towards higher latitudes and higher elevations over the last 45 years. We do this in an occupancy modeling framework (MacKenzie et al., 2018; Mackenzie et al., 2002) where we infer non-detection of a notable species (the bluethroat) by assuming that observers who report less notable 'background' species would also have reported the notable species if it had been seen. In this way, we exploit observer bias towards reporting notable and exciting species to transform opportunistic detection-only data into detection/non-detection (occupancy data), allowing for stronger inference (conditioning on observations of common and less notable species).

The bluethroat, a montane specialist dependent upon the shrubby ecotone between mountain birch forest and tundra, is an interesting species for this work for two reasons. First, its conservation status is somewhat uncertain in this region. Officially, the bluethroat is classified 'least concern' both globally (BirdLife International, 2019) and on national red lists for Norway, Sweden, and Finland (Artdatabanken, 2020; Artsdatabanken, 2021; Hyvärinen et al., 2019). However, there is some evidence that bluethroat abundance may have declined in Norway (Lehikoinen et al., 2014) where the species was red-listed from 2015-2021 (Henrikson and Hilmo, 2015; Artsdatabanken, 2021), and habitat specialists are generally more at risk than generalists (Jiguet et al., 2010). Further, little information exists about changes in the distribution of the bluethroat within Scandinavia over the past few decades (but see (Couet et al., 2022)). Second, the bluethroat has functional traits that suggest opposing expectations about shifts in its geographic range over time. The bluethroat is a long-distance migrant - bluethroats from Scandinavia most likely migrate along the Indo-European flyway and winter in India (Lislevand et al., 2015) - and resident species have been shown to be more likely to shift their ranges over time than migratory species (MacLean and Beissinger, 2017). However, bluethroats are also fairly short-lived and occur at high elevations, both of which may lead to faster uphill shifts (Couet et al., 2022). Thus, our work seeks to fill important knowledge gaps for the bluethroat, as well as improving inferences drawn from opportunistic community science datasets.

2 Materials and Methods

2.1 Study area and observation data

We studied the bluethroat breeding distribution across the Fennoscandian peninsula of northern Europe, including Norway, Sweden, and Finland, and our study period covered the years 1980-2024. To improve computational efficiency, we only included regions where the bluethroat historically breeds; specifically, we included data from all of Norway and we only included data from north of 61° and 65° latitude for Sweden and Finland, respectively. This area comprises >740 000 km^2 and includes the entire range of the Scandinavian Mountains (Scandes), as well as surrounding areas.

We downloaded species observation records from the Global Biodiversity Information Facility (GBIF), and filtered observations to meet our requirements. We downloaded species records from Norway, Sweden, and Finland for the bluethroat and for 12 background species (brambling [*Fringilla montifringilla*], fieldfare [*Turdus pilaris*], hooded crow [*Corvus cornix*], meadow pipit [*Anthus pratensis*], common gull [*Larus canus*], northern wheatear [*Oenanthe oenanthe*], common raven [*Corvus corax*], redshank [*Tringa totanus*], redwing [*Turdus iliacus*], twite [*Carduelis flavirostris*], willow tit [*Poecile montanus*], and willow warbler [*Phylloscopus trochilus*]) using the 'rgbif' package (Chamberlain et al., 2025) in R (R Core Team, 2024). We only included records made by human observers that included coordinates, had no geospatial issues, and had <500m coordinate uncertainty (to match the spatial scale of our study). Our goal was to analyze changes in the bluethroat breeding distribution; therefore, we only included data from 10 June to 14 July in our analysis, a period that reflects the peak of the bluethroat breeding season in Scandinavia. In the end, our data included observations from 27 different datasets, but the vast majority of records came from Artsobservasjoner (56%; https://www.artsobservasjoner.no/) and Artportalen (19%; https://www.artportalen.se/), species reporting services from Norway and Sweden, respectively (?).

To compile records from the bluethroat and background species into detection histories, we overlaid the entire Fennoscandian peninsula with a tesselation of hexagonal grid cells, each of which were 1 km^2 in area. We selected 1 km^2 as the spatial scale to balance the tractability of the analysis with the need to minimize variation in elevation within grid cells, as well as to better capture any uncertainty in the observation locations. Then, we used a spatial join in the 'terra' package (Hijmans, 2024) to assign individual records to the corresponding hexagonal grid cell.

2.2 Occupancy modeling

To create repeated surveys for occupancy modeling, we split our primary season (10 June - 14 July) into five, week-long secondary survey periods (hereafter 'surveys'). We used a 7-day secondary survey period to avoid bias from varying survey effort throughout a week (e.g., surveys are more likely to occur on the weekend). Next, we used observations of background species to infer non-detections of bluethroats. If an observation of any background species was reported in a given grid cell in a given primary season and survey period, then that cell was considered 'surveyed' in that period. If a site was surveyed, it could then receive either a '0' if no bluethroat was reported, or a '1' if a bluethroat was also reported, during the same survey. This method of inferring non-detections relies upon the assumption that an observer who reported a common and drab background species would have also reported a bluethroat, which is brightly-colored and notable in our study region. Grid cells where a bluethroat was reported but no background species were reported were not considered surveyed and were

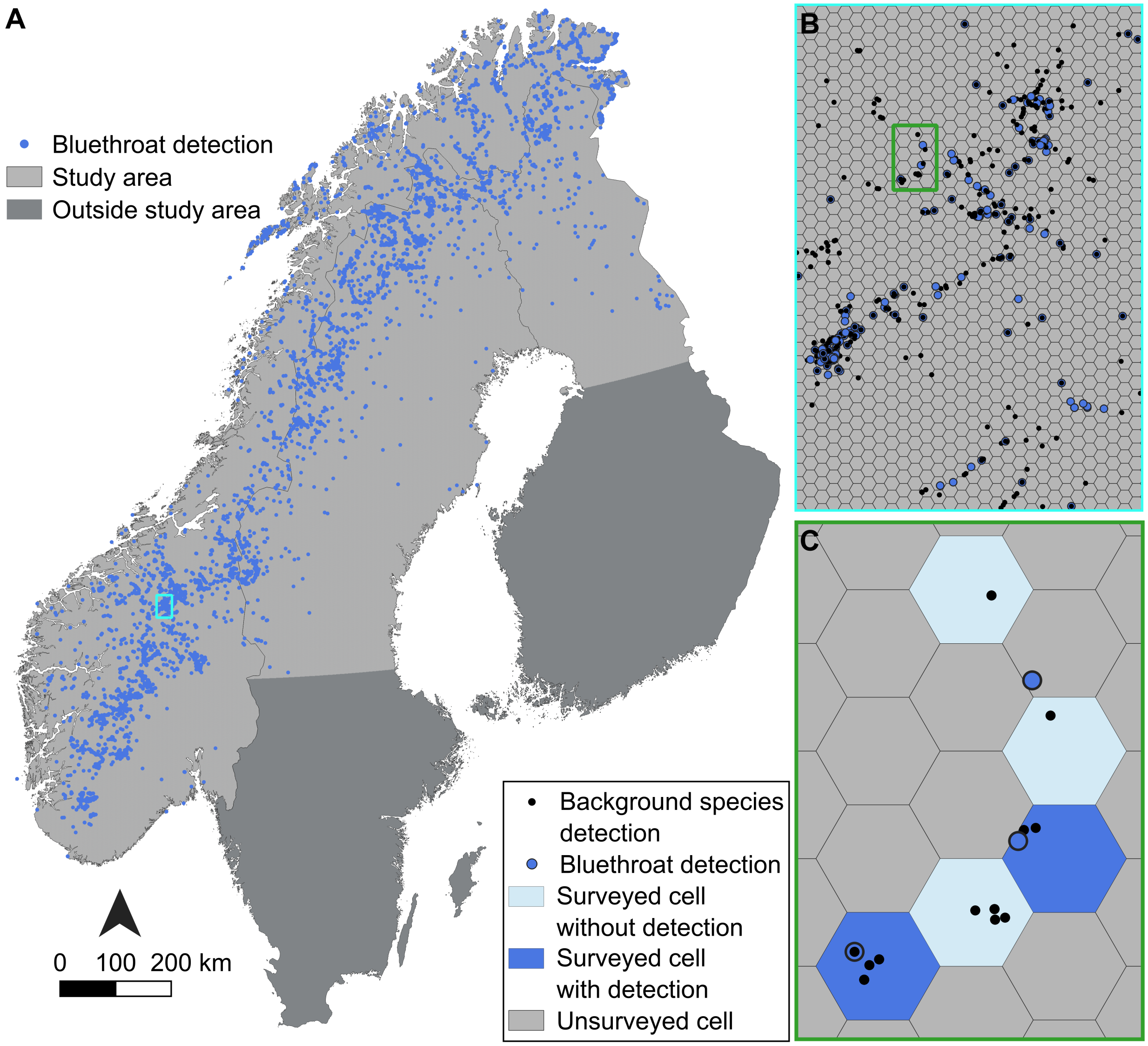

Figure 1: Map of the study area showing how individual observations were compiled to the level of 1-km hexagonal grid cells. (A) The entire study area and all bluethroat observations from the study period (1980-2024). (B) A view of many grid cells, along with observations of both background species (black) and bluethroats (blue). (C) Visualization of compiling observations to the grid cell level. We considered cells to be 'surveyed' (in a given year and survey) if a background species was reported there, and we considered cells to have a bluethroat detection if both a background species and a bluethroat were reported.

treated as missing data (Fig. 1). In this way, the resulting detection/non-detection data only represent site×years where at least one of the background species have been seen, but by using a wide range of common and widely distributed background species (listed above), we still maintain a wide inference space (see Fig. S1).

2.2.1 Occupancy sub-model

To investigate the hypothesis that the bluethroat breeding distribution has shifted northward or upslope over the past 45 years, we used multiseason spatio-temporal occupancy models to estimate occupancy probability depending on elevation, latitude, and time, while accounting for heterogeneity in detection. Elevation and latitude both shape species distributions and also influence each other's relationship with species distributions, so we included elevation, latitude, and the interaction between them in the occupancy sub-model. We used elevation data from a 30-m global Digital Elevation Model with forests and buildings removed (Hawker et al., 2022), and summarized it using the arithmetic mean within each 1-km grid cell (Fig. S2). For latitude, we used the latitude of the centroid of each grid cell. We also included a linear effect of year on the logit scale. Finally, we included the interaction effects 'year*latitude' and 'year*elevation' on occupancy probability to estimate changes in the latitudinal and elevational distribution of bluethroats over the past 45 years. Preliminary data analysis indicated that including elevation as a quadratic predictor may not effectively capture the non-linear relationship between bluethroat occupancy and elevation, and so we first compared two models, one where we modeled elevation with a simple cubic spline and one where we modeled the effect of elevation with a cubic spline and five degrees of freedom (*i.e.*, a cubic spline with two knots) to account for non-linearity in the effect of elevation. Lastly, with the previously determined structure for elevation, we fit a full interaction model with a three-way interaction between year, latitude, and elevation, to investigate to what degree occupancy had changed at a different rate across combinations of latitude and elevation.

Because occupancy dynamics at surveyed locations may not be independent and because our data consisted of repeated surveys at some of the same locations across years, we incorporated independent spatial and temporal random effects (Doser et al., 2022; Diana et al., 2023) in our occupancy sub-model to account for possible spatial and temporal autocorrelation. Specifically, we modeled the site-level effect as a spatial random effect using a nearest neighbor Gaussian Process (Doser et al., 2022; Datta et al., 2016) with an exponential covariance function and 10 nearest neighbors, and we modeled the year-level random effect as an auto-regressive (AR1) structured effect of year. For a more detailed description of the model formulation, see Appendix S1.

2.2.2 Detection sub-model

We also included covariates in the detection sub-model to account for factors impacting the detection probability of bluethroats. First, we included a different intercept for each secondary survey period because vocal behavior of the bluethroats changes across the season, and vocalizing birds are likely to have higher detectability. The detection model also included latitude, elevation, and their interaction, to account for any differences in detectability of bluethroats between denser birch forests present at lower elevations and more open tundra and heathland at higher elevations, a habitat difference which is also mediated by latitude. Lastly, we included an 'effort' covariate, computed as the total number of reports of any background species during the week (survey period), which we used as a proxy of the survey effort. Similar to list length analysis (Szabo et al., 2010), this covariate reflects both how many people visited a given site during a secondary replicate, as well as how much time they spent there, as longer lists (*i.e.*, more reports of background species) are produced when more effort is expended.

2.2.3 Modeling procedure

We implemented all models in the 'spOccupancy' package, v. 0.7.6 (Doser et al., 2022), in the R Statistical Environment (R Core Team, 2024). We specified all fixed parameter priors as $N(0, 2.72)$ Northrup and Gerber (2018). We specified the temporal variance prior as inverse gamma (shape = 2, scale = 0.5), and we specified the temporal decay (*i.e.*, the correlation between random effects that are one year apart) prior as uniform with limits of -1 and 1. For the spatial variance parameter, we specified an inverse gamma prior (shape = 2, scale = 1), and for the spatial decay parameter, we specified a uniform prior with a lower limit of 3 divided by the maximum inter-site distance ($3/1782 = 0.0017$) and an upper limit of 3 divided by the minimum inter-site distance ($3/0.54 = 5.56$), which allowed the effective spatial range (the distance at which spatial correlation between sites is <0.05) to be anywhere between the minimum and the maximum distance between our surveyed sites (0.54 to 1782 km). Before inclusion in models, we centered and standardized latitude, year, and effort (by subtracting the mean and dividing by two times the standard deviation), and we centered elevation on 800 m and standardized it (by subtracting 800 and dividing by two times the standard deviation) to improve model convergence.

We ran 3 chains of 50,000 iterations each, with a burn-in of 30,000 iterations and a thinning rate of 40, for a total of 1500 posterior samples across all chains. We confirmed model convergence using rhat values (confirmed all values were <1.1), as well as examining traceplots of the chains for each parameter, and we conducted posterior predictive checks (grouping by site and by survey) to ensure model adequacy. We used WAIC for all model comparisons, and we selected the model with the lowest WAIC for drawing inference. Except where noted, all results are reported with the posterior mean and 95% credible interval (CRI). We used both the absolute change over time (*i.e.*, probability of occupancy in 2024 minus the probability of occupancy in 1980) and the relative change over time (*i.e.*, the odds ratio 2024/1980) to fully characterize changes in occupancy over time in the context of our hypothesis.

3 Results

3.1 Observation data

Our final dataset included 550,784 observations from 49,455 sites (*i.e.*, 1-km^2 hexagonal grid cells) across Norway, Sweden, and Finland. The number of surveys per year generally increased over the time period of the study (Fig. S3A), as did the number of surveys with bluethroats detected (Fig. S3B). Among the years of the study, the proportion of sites with bluethroat detections ranged from 3% (2024) to 18% (1981), and the average proportion of sites with a bluethroat detection was 7.1% (sd = 3.7%; Fig. S3C)). Our data also included many 'missing' surveys, as most sites were not surveyed every year, and those sites that were surveyed often received effort in only one secondary sampling period (Fig. S4).

3.2 Occupancy

We found that the best structure for the elevation effect included a cubic spline and two knots (ΔWAIC between models = 365), and we found that a model with a three-way interaction between year, latitude, and elevation best modeled changes in breeding season occupancy over the past 45 years (ΔWAIC between two-way and three-way interaction models = 4). Posterior distributions for the occupancy parameters in the final model are in Fig. S5. Posterior predictive checks indicated that model fit was adequate overall. When grouping by site, posterior predictive checks for a handful of years indicated that the model produced data with more variability than we observed, suggesting that credible intervals may be conservative.

Latitude and elevation mediated each other's relationships with occupancy. At low and

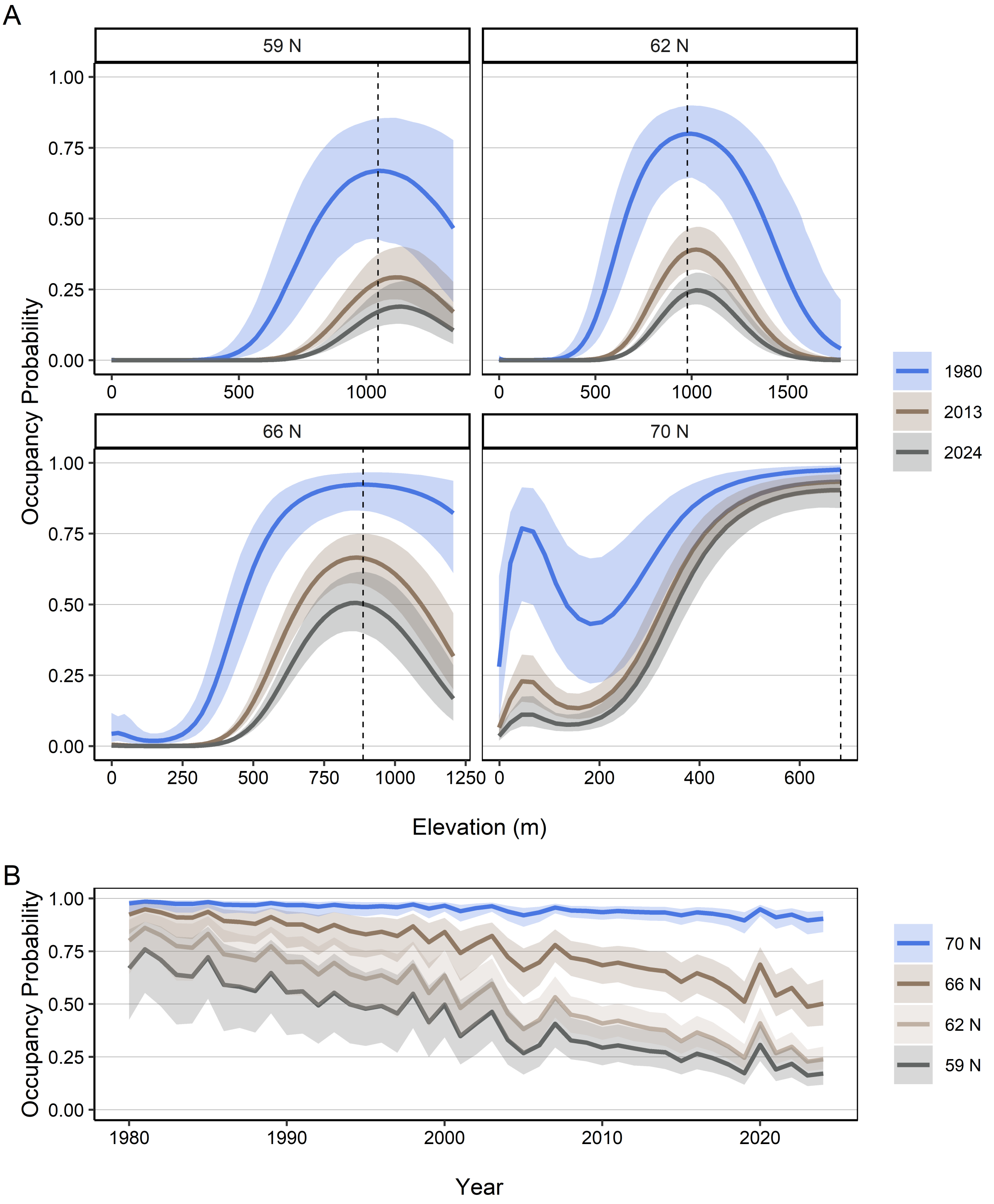

Figure 2: (A) The association between occupancy and elevation at four representative latitudes (panels) and three time steps (colors) with 95% credible intervals. Dashed vertical lines represent the elevation with the highest predicted occupancy at each latitude in 1980 (the first year of the study). (B) For the elevation at each latitude with the peak predicted occupancy in 1980 (dashed vertical lines in A), predicted occupancy over the 45 years of the study with 95% credible intervals.

mid-latitudes, occupancy was typically hump-shaped, reaching a peak at mid-elevations, with the elevation of the peak differing across latitudes. However, at high latitudes, occupancy peaked at high elevations (Fig. 2A). We note that at high latitudes, the range of elevation present in the dataset was from approximately 0 to 800 m, compared to an approximately 1500 m range of elevation at mid-latitudes. At the highest latitudes (*i.e.*, 70-72°N), there was also a smaller peak in occupancy at lower elevations, but this peak was greatly reduced in later years of the study (Fig. 2A). At lower latitudes (*e.g.*, 59°N and 62°N in 2A), we also predicted an upward shift over time in the elevation where the highest predicted occupancy occurred. For example, at 59°N the elevation with the highest predicted occupancy was 1047 m in 1980, but increased to 1138 m by 2024. Similarly, at 62°N, the elevation with highest predicted occupancy shifted from 978 m to 1023 m form 1980 to 2024. However, we saw no change at 70°N, and a subtle downhill shift in the elevation with the peak predicted occupancy at 66°N (887 m to 864 m from 1980 to 2024; 2A).

Occupancy of bluethroats notably declined across Fennoscandia over the 45 years of the study (Fig. 2, Fig. 3, Fig. 4, Fig. 5), and combinations of latitude and elevation played roles in shaping these changes in occupancy (Fig. 3). Considering a site at average latitude (63.6°) and 800 m elevation, the odds of occupancy declined by a factor of 0.94 (or 6%, CRI: 0.92-0.95, 5-8%) after one year, leading to a reduction in the odds of occupancy by a factor of 0.52 (48%, CRI: 0.44-0.60, 40-56%) after 10 years. While occupancy in early years of the study was high across a large swath of latitude/elevation combinations, by 2024, occupancy was typically low below 64° latitude (Fig 3A). Unsurprisingly, model uncertainty was also higher in the early years of the analysis when data were more sparse (Fig 3B). In general, the probability of occupancy declined the most in areas where occupancy was higher at the start of the study (Fig. 3C), but the ratio of the odds of occupancy in 2024 versus 1980 revealed that areas with both low elevation and low latitude were predicted to have the largest relative changes (Fig. 3D). However, many of these sites had low occupancy at the

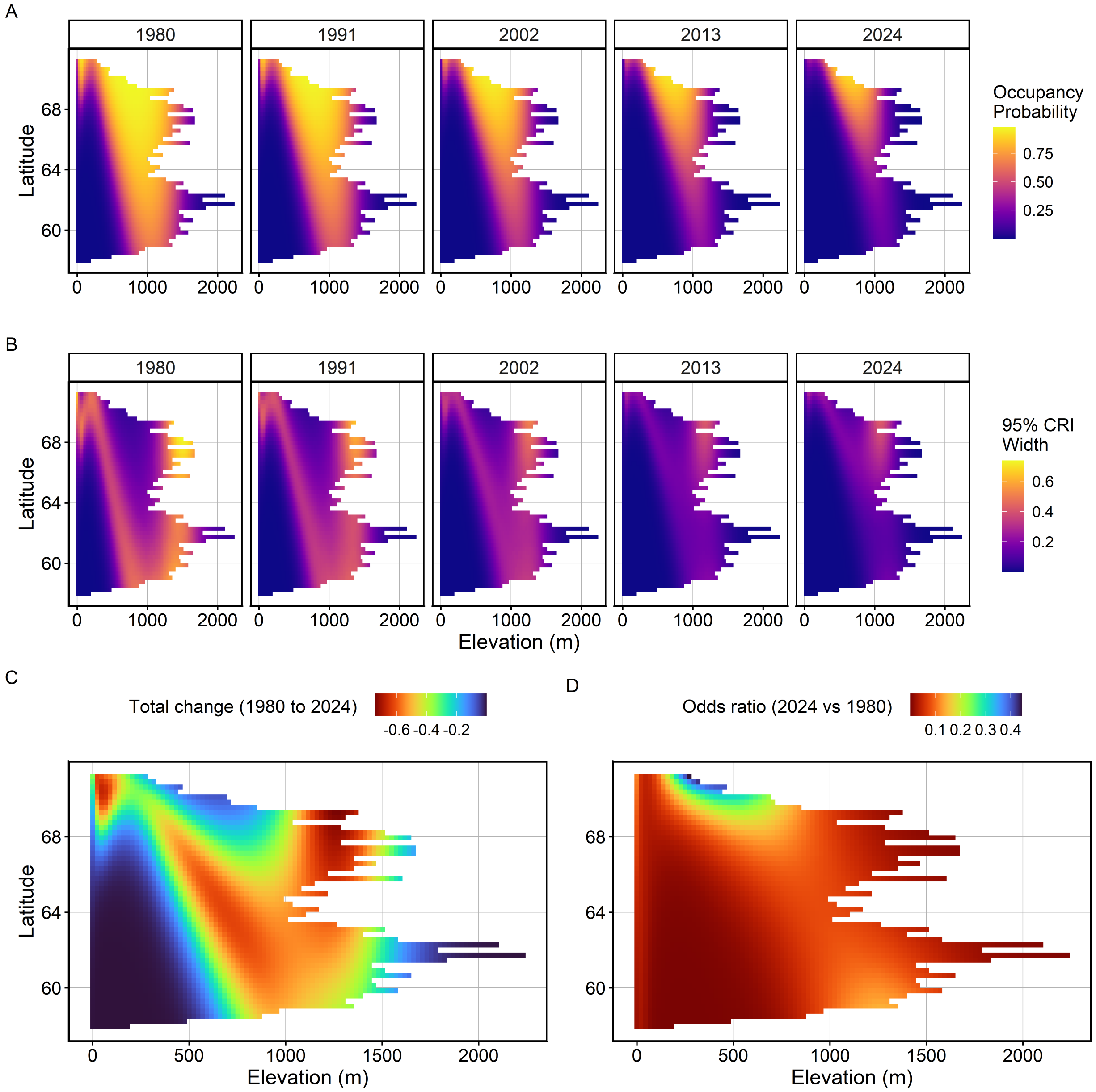

Figure 3: Contour plot showing how bluethroat occupancy probability declined across the range of latitudes and elevations present in the study area from 1980-2024. (A) Bluethroat occupancy probability predicted for five time-steps. (B) The width of the 95% credible intervals for the same 5 time steps. (C) The absolute change in occupancy probability from the first year of the study (1980) to the last year of the study (2024). (D) The ratio of the odds of occupancy for 2024 versus 1980, showing the relative change in occupancy from the beginning to the end of the study.

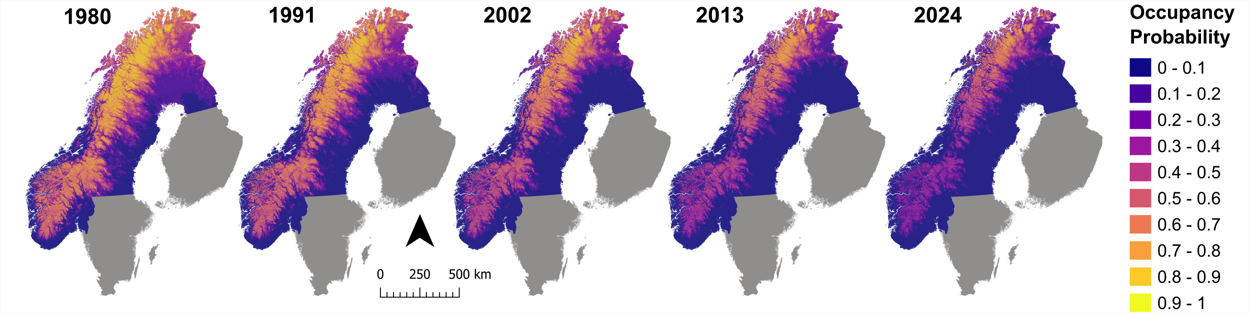

Figure 4: Predicted occupancy probability across the study area for five time-steps of 11 years.

beginning of the study such that occupancy probability changed from close to zero in 1980 to even closer to zero in 2024, and thus the total (absolute) change in occupancy probability was lower in these areas. The odds ratios demonstrated that high latitude sites had lower relative change, as did mid- to high-elevation sites at lower latitudes (Fig. 3D).

Similar patterns were reflected when we estimated occupancy across the Fennoscandian peninsula for the years of the study, but spatial and temporal random effects also contributed to occupancy predictions (Fig. 4). The posterior mean of the spatial variance was 5.24 (95% CRI: 4.51 - 6.08; spatial sd = 2.29, 95% CRI: 2.12-2.47) and the posterior mean of the spatial decay was 0.00169 (95% CRI: 0.00168 - 0.00171) on the logit scale. The posterior for the spatial decay was tightly pushed against against the lower bound. The spatial random effects suggest rather high variance between sites over a large spatial range, which suggests they may reflect environmental factors not accounted for in the fixed part of the model that are themselves auto-correlated. Plots of the spatial random effects show quite localized areas with stronger effects (Fig. S6A). In particular, fixed effects tended to underestimate occupancy in the west and overestimate it in the east (Fig. S6A), which may correspond to specific habitat conditions at these sites such as a lower treeline in the west due to higher winter precipitation. We estimated the posterior mean for the temporal variance as 0.11 (95% CRI 0.06 - 0.21; temporal sd = 0.33, 95% CRI 0.24-0.46), and the temporal decay as

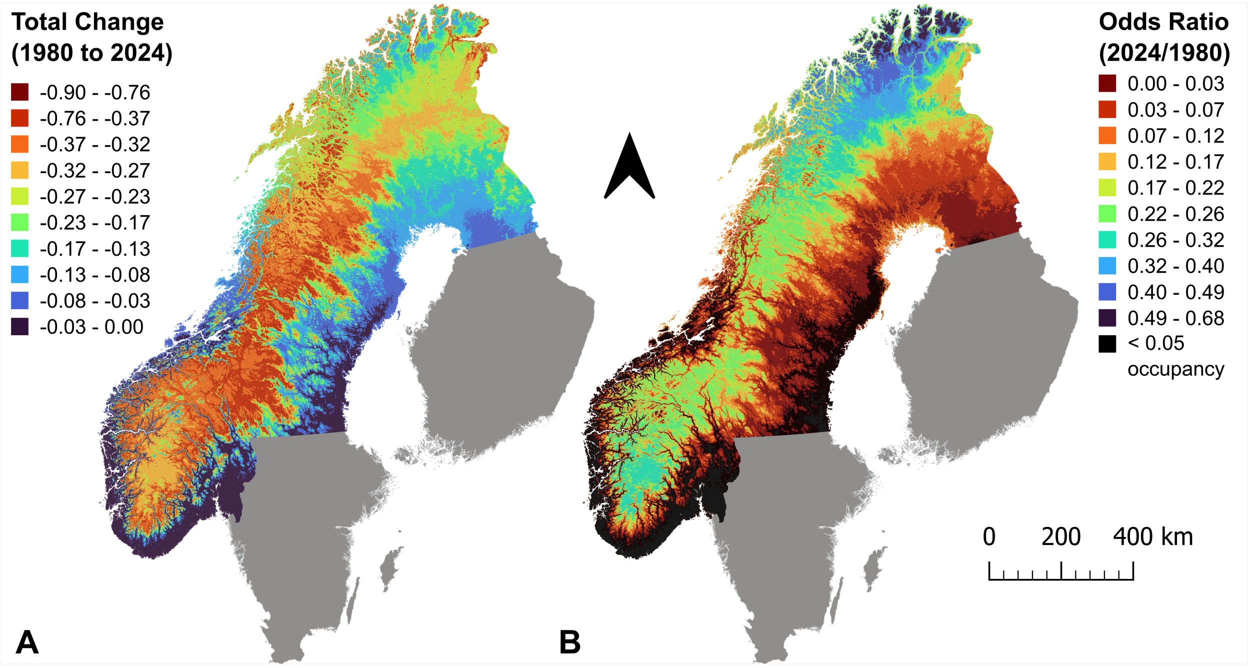

Figure 5: Change in occupancy from the first year of the study (1980) to the last year of the study (2024). (A) The change in the probability of occupancy from 1980 to 2024 showing which areas have experienced the largest absolute declines in probability of occupancy. (B) The ratio of odds for 2024 versus 1980 showing which areas experience the largest relative declines in occupancy. Note that areas with < 0.05 (5%) predicted probability of occupancy in 1980 are masked with black to aid interpretation.

-0.04 (95% CRI -0.3 - 0.23). These estimates corresponded to small temporal random effects where the 95% CRI usually overlapped zero (Fig. S6B). In the context of these effects, our model indicates that occupancy has declined across the entire study area, with the largest absolute changes in occupancy probability occurring at low- to mid-latitude sites and in coastal areas in the far north (Fig. 5A). Some strongholds of higher occupancy remain in the north, particularly in Troms and Finnmark in Norway and Lappland in Sweden, and in smaller localized pockets of mid- to high elevation at low- to mid-latitudes in southern Norway, where odds ratios indicate that occupancy is changing more slowly (Fig. 5B).

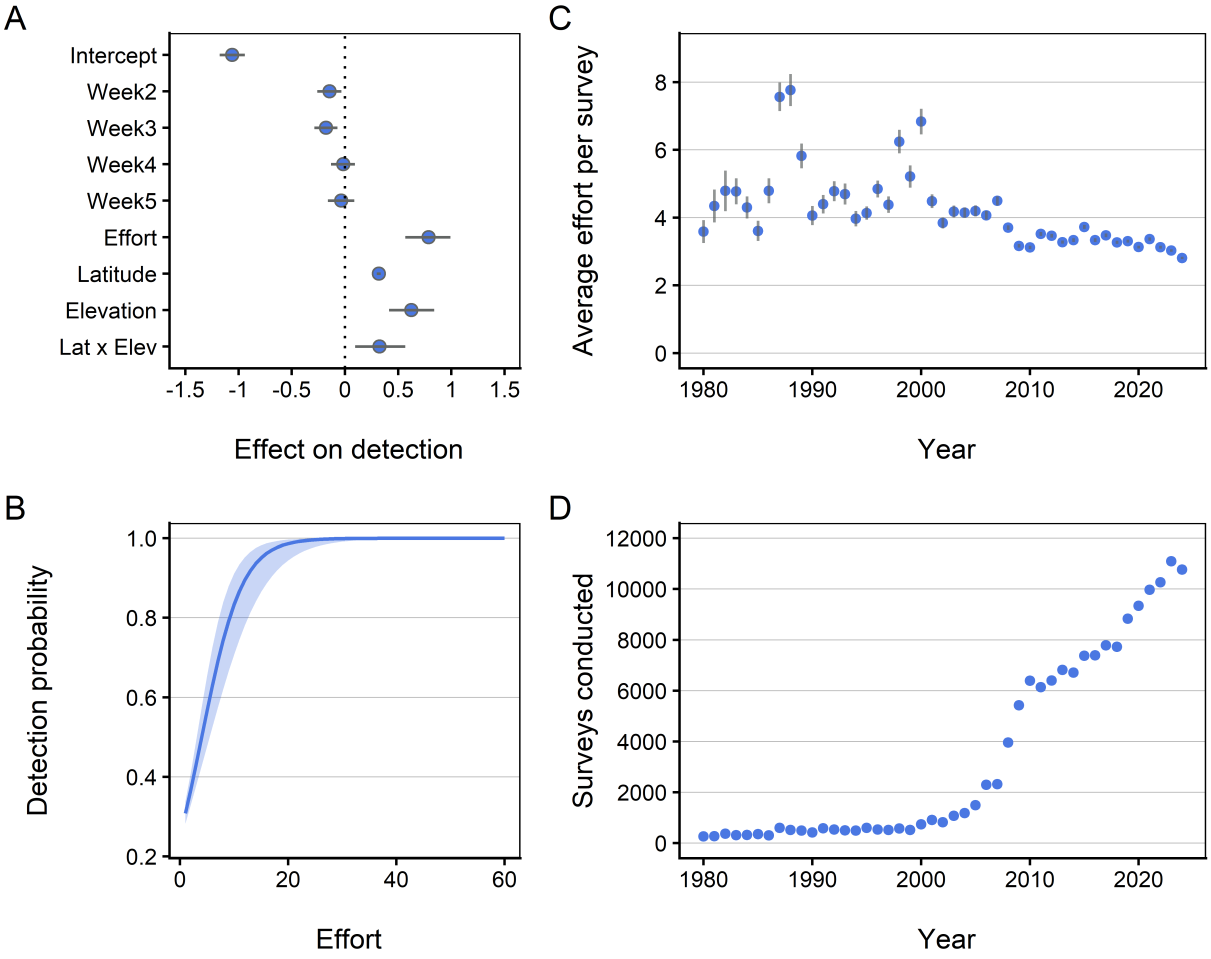

Figure 6: (A) Effect size and 95% credible interval for all parameters in the detection submodel (logit scale; units are change per two standard deviation change in the predictor). (B) The association between effort and detection probability, where effort is measured as the number of reports of background species during a given survey. (C) Average effort (number of reports of background species) per survey in each year, represented by the mean and standard error across all 49,455 survey sites. (D) The count of the number of surveys conducted in each year of the study.

3.3 Detection

Detection probability at an average site (*i.e.,* 63.6° latitude, mean effort, 800 m elevation) ranged from 0.22 in week 3 to 0.26 in week 1, and effort, latitude, elevation, and the interaction between latitude and elevation all had positive effects on detection probability (Fig. 6A). Effort, in particular, showed a strong positive relationship with detection probability, such that more than 20 reports of background species within a given secondary sampling period resulted in nearly perfect detection of bluethroats (Fig. 6B). However, most sites received considerably less effort than that. Average effort (number of reports of background species per survey) ranged from 2.8 (in 2024) to 7.8 (in 1988) reports (Fig. 6C). Notably, the number of surveys conducted increased substantially over the years (Fig. 6D). Most surveyed sites were only surveyed once in a given year (Fig. S4), and many sites only received effort in a small number of years.

4 Discussion

The declines we observed in bluethroat occupancy largely coincide with expectations under climate change - sites at higher latitudes and higher elevations generally experienced smaller relative declines occupancy (*i.e.*, had higher odds ratios). However, high latitude sites and high elevation sites at lower latitudes also often had higher occupancy probability to begin with, leading to these areas also experiencing some of the highest absolute declines in occupancy probability over the course of our study. In essence, these results suggest that areas at high latitudes and high elevations at low to mid-latitudes function as refugia where occupancy changes more slowly, but occupancy is declining even in these refugia. Upward shifts in peak occupancy towards higher elevations in the southern portions of the study area further support the role of climate change in the decline.

Notably, we only observed declines in occupancy over time, never increases. Overall, the amount of habitat occupied by breeding bluethroats declined dramatically across the 45 years of our study. This pattern matches the expectation for many montane organisms - species already living at high altitudes may not have anywhere to shift to as climate change progresses, termed the 'escalator to extinction' (Urban, 2018; Marris, 2007; Sekercioglu et al., 2008). The decline we documented in bluethroat occupancy is a reminder that even 'common' species are under threat from climate change, a pattern also reflected in other areas (Inger et al., 2015; Dupont and Dobson, 2025).

While we examined occupancy and not abundance, given the generally positive relationship between abundance and occupancy (Gaston et al., 2000; Zuckerberg et al., 2009) especially among long-distance migrants (Manne and Veit, 2020), it is probable that the decline in occupancy we observed over the 45 years of our study is accompanied by reduced abundance, as well. Structured monitoring data from 2002 to 2012(Lehikoinen et al., 2014) and 2002 to 2014 (Lehikoinen et al., 2019) indicated non-significant declines in bluethroat abundance across Fennoscandia, with some evidence of a small decline in Norway 2002 to 2012. The longer temporal scale and the high spatial resolution of our study provides more context for these analyses. It is possible that bluethroat abundance declined more quickly in the early part of our study period before stabilizing in the latter period, but the temporal random effects (Fig . S5B) do not seem to indicate this pattern. Another hint at a waning source population is the steady decline of a peripheral population of red-spotted bluethroats in the Krkonoše Mountains, Czech Republic, which is dependent upon immigration from populations in Sweden and Norway (Damnjanović et al., 2024; Johnsen et al., 2006), to only a few breeding pairs (Damnjanović et al., 2024). Notably, the white-spotted bluethroat (*Luscinia svecica cyanecula*), which breeds in lowland wetlands throughout Central Europe, is experiencing a population and range expansion and has even established a breeding population in southern Sweden (Andersson, 2022; Petras and Vrezec, 2022).

Our results suggest that climate change may play some role in declining bluethroat occupancy, but the question remains what proximate factors are responsible for the decline. Climate change can affect species directly through abiotic mechanisms (e.g. heat stress, drought stress, etc.), but also, and perhaps even more importantly, indirectly through biotic mechanisms such as phenological mismatches, novel interactions with species shifting or expanding their ranges, or changes in prey availability (Cahill et al., 2013; Ockendon et al., 2014). Changes to breeding habitat may be one important factor to consider. Bluethroats are habitat specialists whose breeding distribution is dependent upon the ecotone between mountain birch forest and tundra. This ecotone is, in turn, shaped by complicated dynamics between climate, herbivory and domestic grazing, topography, and vegetation (Bryn and Potthoff, 2018; Mienna et al., 2024; Speed et al., 2010) and is rapidly changing in some areas, with advancing treelines and loss of tundra occurring more rapidly in southern Fennoscandia (Nygaard et al., 2022; Hofgaard et al., 2009). Bluethroats are also insectivores, which are declining across Europe (Bowler et al., 2019), and long-distance migrants, which may be less able to shift their breeding phenology to match changing spring phenology (Both et al., 2006; Søraker et al., 2022), leading to declining populations ((Møller et al., 2008; Both et al., 2006), but see also Knudsen et al. (2011)). Interestingly, studies in the region have shown that long-distance migrants do not have more negative population trends than short-distance or resident species (Lehikoinen et al., 2014) and that migratory behavior is not as good a predictor of altitudinal range shifts as life history (Couet et al., 2022). In summary, more work, likely across multiple spatial scales, is necessary to identify depressed vital rates (*e.g.*, adult survival, fecundity, etc.) and establish causal relationships between bluethroat declines and proximate mechanisms.

To our knowledge, this the first study to exploit bias towards reporting 'notable' (*e.g.*, rare, exciting, or culturally important) species to construct non-detections, and our results demonstrate that unstructured community science data can fill important knowledge gaps about population trends across space and time. Occupancy models are a robust method for drawing inference from messy community science datasets (Johnston et al., 2021; Isaac et al., 2014; Hochachka et al., 2023), especially because they allow for the inclusion of covariates that describe the detection process. Given its positive association with detection probability, the number of observations of background species reported was seemingly a reasonable proxy for survey effort, the inclusion of which likely also helped account for the general increase in survey effort across the 45 years of the study. Furthermore, the somewhat low detection probability (< 0.3) and strong covariate effects in our study underscore the importance of correcting for imperfect detection. However, information about non-detections is required in order to take advantage of this powerful class of models, and many readily-available community science datasets are detection-only.

It is obviously most desirable to have data where non-detections are explicitly recorded, such as when reported data are guaranteed to be 'complete checklists'(Johnston et al., 2021; Kéry et al., 2010). However, when databases do not include information about whether 'complete checklists' are reported or not, as has until recently been the case for the Norwegian and Swedish reporting portals, we believe that our approach of inferring non-detections from the reporting of much less 'notable' species is robust. van Strien et al. (2010, 2013) also constructed non-detections from detection-only data, but they used reports of any other dragonfly species to infer non-detections of focal dragonfly species (van Strien et al., 2010, 2013). This assumption may hold for dragonflies, where an observer with knowledge of one species may be assumed to have knowledge of others, but it is likely less valid for birds where observers with little experience may be more likely to report a bright and easy-to-identify species and many observers may be more likely to report rare or exciting species (Backstrom et al., 2025). In our specific application, we find it highly unlikely that birders who report any of the background species would *not* report the iconic bluethroat if observed. It is also important to note that such cases would only contribute to lower detection probability and not bias the occupancy estimates, as long as the model captures the major sources of variation in detection probability. One probable source of bias, however, is the the tendency of observers to initiate a checklist list only after seeing a notable species (Backstrom et al., 2025). This would lead to an over-representation of checklists that include the notable focal species also among checklists that include the less notable background species. This tendency could lead to an overestimation of occupancy; however, large scale geographic and temporal patterns will only be biased if the over-representation is substantially different in different regions, or changes systematically over time. We do not see any reasons for this being the case in our study.

The obvious limitation of our method is that it can only be applied to 'notable' species; however, 'notable' species are often those that researchers may be explicitly interested in modeling due to protected status, rarity, or cultural importance. We demonstrated the method here for just one notable species in the Fennoscandian peninsula, but this method could be applied to any notable species of any taxa or geographic distribution where the assumption applies.

5 Conclusions

Unstructured community science data are readily available in large quantities and across large spatial and temporal extents, but they are also subject to many potential biases (Johnston et al., 2021; Bird et al., 2014). Variability in observer behavior is a central challenge to maximizing the utility of unstructured community science data (Johnston et al., 2023; Schmidt et al., 2023), but the number of studies explicitly focused on understanding the behavior of contributors to community science databases is increasing (Kolstoe and Cameron, 2017; Backstrom et al., 2025; Tulloch and Szabo, 2012; Callaghan et al., 2021; Bowler et al., 2022). The power of unstructured data to detect trends will always be lower than that of structured data resulting from well-designed survey protocols (Kamp et al., 2016; Altwegg and Nichols, 2019); however, our results demonstrate that an understanding of the biases present in community science data can be leveraged to take advantage of these massive datasets. Our uncovering of a decline in bluethroat occupancy over the past 45 years further demonstrates that these data can be used to fill important knowledge gaps about species trends in light of rapid global change.

References

Altwegg, R., and J. D. Nichols, 2019: Occupancy models for citizen-science data. *Methods in Ecology and Evolution*, **10 (1)**, 8–21, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/2041-210X.13090.

Andersson, R., 2022: Invandringsförloppet hos vitstjärnig blåhake Luscinia svecica cyanecula på svenska västkusten. *Ornis Svecica*, **32**, 5–13,

Archaux, F., 2004: Breeding upwards when climate is becoming warmer: no bird response in the French Alps. *Ibis*, **146 (1)**, 138–144, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1474-919X.2004.00246.x.

Artdatabanken, S., 2020: Rödlistade arter i Sverige 2020. Tech. rep., SLU, Uppsala, 242 pp.

Artsdatabanken, 2021: Norsk rødliste for arter 2021. Tech. rep., Artsdatabanken, Trondheim, 210 pp.

Backstrom, L. J., R. L. Drake, H. Worthington, and A. Johnston, 2025: Detections of Rare Species Lead Citizen Scientists to Initiate Data Recording. *Diversity and Distributions*, **31 (10)**, e70 103,

Bateman, B. L., A. M. Pidgeon, V. C. Radeloff, J. VanDerWal, W. E. Thogmartin, S. J. Vavrus, and P. J. Heglund, 2016: The pace of past climate change vs. potential bird distributions and land use in the United States. *Global Change Biology*, **22 (3)**, 1130–1144, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/gcb.13154.

Bird, T. J., and Coauthors, 2014: Statistical solutions for error and bias in global citizen science datasets. *Biological Conservation*, **173**, 144–154,

BirdLife International, 2019: Luscinia svecica. Tech. rep., Both, C., S. Bouwhuis, C. M. Lessells, and M. E. Visser, 2006: Climate change and population declines in a long-distance migratory bird. *Nature*, **441 (7089)**, 81–83,

Bowler, D. E., H. Heldbjerg, A. D. Fox, M. de Jong, and K. Böhning-Gaese, 2019: Long-term declines of European insectivorous bird populations and potential causes. *Conservation Biology*, **33 (5)**, 1120–1130, , _eprint: https://conbio.onlinelibrary.wiley.com/doi/pdf/10.1111/cobi.13307.

Bowler, D. E., and Coauthors, 2022: Decision-making of citizen scientists when recording species observations. *Scientific Reports*, **12 (1)**, 11 069,

Bryn, A., and K. Potthoff, 2018: Elevational treeline and forest line dynamics in Norwegian mountain areas – a review. *Landscape Ecology*, **33 (8)**, 1225–1245,

Cahill, A. E., and Coauthors, 2013: How does climate change cause extinction? *Proceedings of the Royal Society B: Biological Sciences*, **280 (1750)**, 20121 890,

Callaghan, C. T., A. G. B. Poore, M. Hofmann, C. J. Roberts, and H. M. Pereira, 2021: Large-bodied birds are over-represented in unstructured citizen science data. *Scientific Reports*, **11 (1)**, 19 073,

Chamberlain, S., V. Barve, D. McGlinn, D. Oldoni, P. Desmet, L. Geffert, and K. Ram, 2025:

Chen, I.-C., J. K. Hill, R. Ohlemüller, D. B. Roy, and C. D. Thomas, 2011: Rapid Range Shifts of Species Associated with High Levels of Climate Warming. *Science*, **333 (6045)**, 1024–1026,

Couet, J., E.-L. Marjakangas, A. Santangeli, J. A. Kålås, Lindström, and A. Lehikoinen, 2022: Short-lived species move uphill faster under climate change. *Oecologia*, **198 (4)**, 877–888, doi:10.1007/s00442-021-05094-4.

Damnjanović, D., M. Nazarizadeh, M. M. Wisniewska, V. Pavel, B. Chutný, A. Johnsen, M. Nováková, and J. Štefka, 2024: Limited genetic depletion despite extinction risk: genomic diversity of a peripheral population of red-spotted bluethroats in Central Europe. *Zoological Journal of the Linnean Society*, **201 (4)**, zlae094,

Datta, A., S. Banerjee, A. O. Finley, and A. E. Gelfand, 2016: Hierarchical Nearest-Neighbor Gaussian Process Models for Large Geostatistical Datasets. *Journal of the American Statistical Association*, **111 (514)**, 800–812,

Diana, A., E. B. Dennis, E. Matechou, and B. J. T. Morgan, 2023: Fast Bayesian inference for large occupancy datasets. *Biometrics*, **79 (3)**, 2503–2515,

Doser, J. W., A. O. Finley, M. Kéry, and E. F. Zipkin, 2022: spOccupancy: An R package for single-species, multi-species, and integrated spatial occupancy models. *Methods in Ecology and Evolution*, **13 (8)**, 1670–1678,

Dupont, G., and A. Dobson, 2025: North American bird declines are driven by reductions in common species. *Science Advances*, **11 (31)**, eadw8971,

Finley, A. O., A. Datta, B. D. Cook, D. C. Morton, H. E. Andersen, and S. Banerjee, 2019: Efficient Algorithms for Bayesian Nearest Neighbor Gaussian Processes. *Journal of Computational and Graphical Statistics*, **28 (2)**, 401–414, , _eprint: https://doi.org/10.1080/10618600.2018.1537924.

Gaston, K. J., T. M. Blackburn, J. J. Greenwood, R. D. Gregory, R. M. Quinn, and J. H. Lawton, 2000: Abundance–occupancy relationships. *Journal of Applied Ecology*, **37 (s1)**, 39–59, , _eprint: https://besjournals.onlinelibrary.wiley.com/doi/pdf/10.1046/j.1365-2664.2000.00485.x.

Hawker, L., P. Uhe, L. Paulo, J. Sosa, J. Savage, C. Sampson, and J. Neal, 2022: A 30 m global map of elevation with forests and buildings removed. *Environmental Research Letters*, **17 (2)**, 024 016,

Henrikson, S., and O. Hilmo, 2015: Norsk rødliste for arter 2015. Tech. rep., Artsdatabanken, Norge, 193 pp.

Hickling, R., D. B. Roy, J. K. Hill, R. Fox, and C. D. Thomas, 2006: The distributions of a wide range of taxonomic groups are expanding polewards. *Global Change Biology*, **12 (3)**, 450–455, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-2486.2006.01116.x.

Hijmans, R. J., 2024:

Hochachka, W. M., D. Fink, R. A. Hutchinson, D. Sheldon, W.-K. Wong, and S. Kelling, 2012: Data-intensive science applied to broad-scale citizen science. *Trends in Ecology & Evolution*, **27 (2)**, 130–137,

Hochachka, W. M., V. Ruiz-Gutierrez, and A. Johnston, 2023: Considerations for fitting occupancy models to data from eBird and similar volunteer-collected data. *Ornithology*, **140 (4)**, ukad035,

Hofgaard, A., L. Dalen, and H. Hytteborn, 2009: Tree recruitment above the treeline and potential for climate-driven treeline change. *Journal of Vegetation Science*, **20 (6)**, 1133–1144,

Hovick, T. J., B. W. Allred, D. A. McGranahan, M. W. Palmer, R. Dwayne Elmore, and S. D. Fuhlendorf, 2016: Informing conservation by identifying range shift patterns across breeding habitats and migration strategies. *Biodiversity and Conservation*, **25 (2)**, 345–356, Hughes, L., 2000: Biological consequences of global warming: is the signal already apparent? *Trends in Ecology & Evolution*, **15 (2)**, 56–61,

Hyvärinen, E., A. Juslén, E. Kemppainen, A. Uddström, and U.-M. Liukko, 2019: The 2019 Red List of Finnish Species. Tech. rep., Ympäristöministeriö & Suomen ympäristökeskus, Helsinki, 704 pp.

Hällfors, M. H., and Coauthors, 2024: Recent range shifts of moths, butterflies, and birds are driven by the breadth of their climatic niche. *Evolution Letters*, **8 (1)**, 89–100,

Inger, R., R. Gregory, J. P. Duffy, I. Stott, P. Voříšek, and K. J. Gaston, 2015: Common European birds are declining rapidly while less abundant species' numbers are rising. *Ecology Letters*, **18 (1)**, 28–36, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ele.12387.

Isaac, N. J. B., A. J. van Strien, T. A. August, M. P. de Zeeuw, and D. B. Roy, 2014: Statistics for citizen science: extracting signals of change from noisy ecological data. *Methods in Ecology and Evolution*, **5 (10)**, 1052–1060, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/2041-210X.12254.

Jiguet, F., R. D. Gregory, V. Devictor, R. E. Green, P. Voříšek, A. Van Strien, and D. Couvet, 2010: Population trends of European common birds are predicted by characteristics of their climatic niche. *Global Change Biology*, **16 (2)**, 497–505,

Johnsen, A., and Coauthors, 2006: Molecular and phenotypic divergence in the bluethroat (Luscinia svecica) subspecies complex. *Molecular Ecology*, **15 (13)**, 4033–4047, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1365-294X.2006.03075.x.

Johnston, A., E. Matechou, and E. B. Dennis, 2023: Outstanding challenges and future directions for biodiversity monitoring using citizen science data. *Methods in Ecology and Evolu-*

tion, **14 (1)**, 103–116, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/2041-210X.13834.

Johnston, A., and Coauthors, 2021: Analytical guidelines to increase the value of community science data: An example using eBird data to estimate species distributions. *Diversity and Distributions*, **27 (7)**, 1265–1277,

Johnston, A., and Coauthors, 2025: North American bird declines are greatest where species are most abundant. *Science*, **388 (6746)**, 532–537,

Kamp, J., S. Oppel, H. Heldbjerg, T. Nyegaard, and P. F. Donald, 2016: Unstructured citizen science data fail to detect long-term population declines of common birds in Denmark. *Diversity and Distributions*, **22 (10)**, 1024–1035, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/ddi.12463.

Knudsen, E., and Coauthors, 2011: Challenging claims in the study of migratory birds and climate change. *Biological Reviews*, **86 (4)**, 928–946, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1469-185X.2011.00179.x.

Kolstoe, S., and T. A. Cameron, 2017: The Non-market Value of Birding Sites and the Marginal Value of Additional Species: Biodiversity in a Random Utility Model of Site Choice by eBird Members. *Ecological Economics*, **137**, 1–12,

Kéry, M., J. A. Royle, H. Schmid, M. Schaub, B. Volet, G. Häfliger, and N. Zbinden, 2010: Site-Occupancy Distribution Modeling to Correct Population-Trend Estimates Derived from Opportunistic Observations. *Conservation Biology*, **24 (5)**, 1388–1397, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1523-1739.2010.01479.x.

Lehikoinen, A., M. Green, M. Husby, J. A. Kålås, and Lindström, 2014: Common montane birds are declining in northern Europe. *Journal of Avian Biology*, **45 (1)**, 3–14, , _eprint: https://nsojournals.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1600-048X.2013.00177.x.

Lehikoinen, A., and Coauthors, 2019: Declining population trends of European mountain birds. *Global Change Biology*, **25 (2)**, 577–588, doi:10.1111/gcb.14522.

Lenoir, J., and J.-C. Svenning, 2015: Climate-related range shifts – a global multidimensional synthesis and new research directions. *Ecography*, **38 (1)**, 15–28, , _eprint: https://nsojournals.onlinelibrary.wiley.com/doi/pdf/10.1111/ecog.00967.

Lenoir, J., and Coauthors, 2010: Going against the flow: potential mechanisms for unexpected downslope range shifts in a warming climate. *Ecography*, **33 (2)**, 295–303, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1600-0587.2010.06279.x.

Lislevand, T., B. Chutný, I. Byrkjedal, V. Pavel, M. Briedis, P. Adamik, and S. Hahn, 2015: Red-spotted Bluethroats Luscinia s. svecica migrate along the Indo-European flyway: a geolocator study. *Bird Study*, **62 (4)**, 508–515, , _eprint: https://doi.org/10.1080/00063657.2015.1077781.

Mackenzie, D. I., J. D. Nichols, G. B. Lachman, S. Droege, J. Andrew, and C. a. Langtimm, 2002: Estimating Site Occupancy Rates When Detection Probabilities Are Less Than One. **83 (8)**, 2248–2255.

MacKenzie, D. I., J. D. Nichols, A. Royle, K. H. Pollock, L. L. Bailey, and J. E. Hines, 2018: *Occupancy Estimation and Modeling*. Elsevier Academic Press.

MacLean, S. A., and S. R. Beissinger, 2017: Species' traits as predictors of range shifts under contemporary climate change: A review and meta-analysis. *Global Change Biology*, **23 (10)**, 4094–4105, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/gcb.13736.

Manne, L. L., and R. R. Veit, 2020: Temporal changes in abundance–occupancy relationships over 40 years. *Ecology and Evolution*, **10 (2)**, 602–611, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/ece3.5505.

Marris, E., 2007: The escalator effect. *Nature Climate Change*, **1 (712)**, 94–96,

Mienna, I. M., K. Klanderud, E. Næsset, T. Gobakken, and O. M. Bollandsås, 2024: Quantifying the roles of climate, herbivory, topography, and vegetation on tree establishment in the treeline ecotone. *Ecosphere*, **15 (4)**, e4845, , _eprint: https://esajournals.onlinelibrary.wiley.com/doi/pdf/10.1002/ecs2.4845.

Møller, A. P., D. Rubolini, and E. Lehikoinen, 2008: Populations of migratory bird species that did not show a phenological response to climate change are declining. *Proceedings of the National Academy of Sciences*, **105 (42)**, 16 195–16 200,

Northrup, J. M., and B. D. Gerber, 2018: A comment on priors for Bayesian occupancy models. *PLOS ONE*, **13 (2)**, e0192 819,

Nygaard, P. H., F. Bøhler, B.-H. Øyen, and B. Tveite, 2022: Long-term spatiotemporal dynamics in a mountain birch (Betula pubescens ssp. czerepanovii) forest in south-east Norway. *Plant-Environment Interactions*, **3 (4)**, 155–169, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1002/pei3.10087.

Ockendon, N., and Coauthors, 2014: Mechanisms underpinning climatic impacts on natural populations: altered species interactions are more important than direct effects. *Global Change Biology*, **20 (7)**, 2221–2229, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/gcb.12559.

Parmesan, C., and G. Yohe, 2003: A globally coherent fingerprint of climate change impacts across natural systems. *Nature*, **421**, 37–42,

Petras, T., and A. Vrezec, 2022: Long-Term Ringing Data on Migrating Passerines Reveal Overall Avian Decline in Europe. *Diversity*, **14 (11)**, 905, Pocock, M. J. O., J. C. Tweddle, J. Savage, L. D. Robinson, and H. E. Roy, 2017: The diversity and evolution of ecological and environmental citizen science. *PLOS ONE*, **12 (4)**, e0172 579,

R Core Team, 2024: R: A language and environment for statistical computing.

Rantanen, M., A. Y. Karpechko, A. Lipponen, K. Nordling, O. Hyvärinen, K. Ruosteenoja, T. Vihma, and A. Laaksonen, 2022: The Arctic has warmed nearly four times faster than the globe since 1979. *Communications Earth & Environment*, **3 (1)**, 1–10,

Rosenberg, K. V., and Coauthors, 2019: Decline of the North American avifauna. *Science*, **366 (6461)**, 120–124, doi:10.1126/science.aaw1313.

Sauer, J. R., and Coauthors, 2017: The first 50 years of the North American Breeding Bird Survey. *The Condor*, **119 (3)**, 576–593,

Schmidt, B. R., S. S. Cruickshank, C. Bühler, and A. Bergamini, 2023: Observers are a key source of detection heterogeneity and biased occupancy estimates in species monitoring. *Biological Conservation*, **283**, 110 102,

Sekercioglu, C. H., S. H. Schneider, J. P. Fay, and S. R. Loarie, 2008: Climate Change, Elevational Range Shifts, and Bird Extinctions. *Conservation Biology*, **22 (1)**, 140–150, , _eprint: https://conbio.onlinelibrary.wiley.com/doi/pdf/10.1111/j.1523-1739.2007.00852.x.

Soroye, P., N. Ahmed, and J. T. Kerr, 2018: Opportunistic citizen science data transform understanding of species distributions, phenology, and diversity gradients for global change research. *Global Change Biology*, **24 (11)**, 5281–5291, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1111/gcb.14358.

Speed, J. D. M., G. Austrheim, A. J. Hester, and A. Mysterud, 2010: Experimental evidence for herbivore limitation of the treeline. *Ecology*, **91 (11)**, 3414–3420, , _eprint: https://esajournals.onlinelibrary.wiley.com/doi/pdf/10.1890/09-2300.1.

Stuecker, M. F., and Coauthors, 2018: Polar amplification dominated by local forcing and feedbacks. *Nature Climate Change*, **8 (12)**, 1076–1081,

Szabo, J. K., P. A. Vesk, P. W. J. Baxter, and H. P. Possingham, 2010: Regional avian species declines estimated from volunteer-collected long-term data using List Length Analysis. *Ecological Applications*, **20 (8)**, 2157–2169, , _eprint: https://onlinelibrary.wiley.com/doi/pdf/10.1890/09-0877.1.

Søraker, J. S., and Coauthors, 2022: Resident bird species track inter-annual variation in spring phenology better than long-distance migrants in a subalpine habitat. *Climate Change Ecology*, **3**, 100 050,

Theobald, E. J., and Coauthors, 2015: Global change and local solutions: Tapping the unrealized potential of citizen science for biodiversity research. *Biological Conservation*, **181**, 236–244,

Thomas, C. D., and J. J. Lennon, 1999: Birds extend their ranges northwards. *Nature*, **399 (6733)**, 213–213,

Tsiftsis, S., Z. Štípková, M. Rejmánek, and P. Kindlmann, 2024: Predictions of species distributions based only on models estimating future climate change are not reliable. *Scientific Reports*, **14 (1)**, 25 778,

Tulloch, A. I. T., and J. K. Szabo, 2012: A behavioural ecology approach to understand volunteer surveying for citizen science datasets. *Emu - Austral Ornithology*, **112 (4)**, 313–325, Urban, M. C., 2018: Escalator to extinction. *Proceedings of the National Academy of Sciences*, **115 (47)**, 11 871–11 873,

van Strien, A. J., T. Termaat, D. Groenendijk, V. Mensing, and M. Kéry, 2010: Site-occupancy models may offer new opportunities for dragonfly monitoring based on daily species lists. *Basic and Applied Ecology*, **11 (6)**, 495–503,

van Strien, A. J., C. A. van Swaay, and T. Termaat, 2013: Opportunistic citizen science data of animal species produce reliable estimates of distribution trends if analysed with occupancy models. *Journal of Applied Ecology*, **50 (6)**, 1450–1458,

VanDerWal, J., H. T. Murphy, A. S. Kutt, G. C. Perkins, B. L. Bateman, J. J. Perry, and A. E. Reside, 2013: Focus on poleward shifts in species' distribution underestimates the fingerprint of climate change. *Nature Climate Change*, **3 (3)**, 239–243,

Walther, G.-R., 2010: Community and ecosystem responses to recent climate change. *Philosophical Transactions of the Royal Society B: Biological Sciences*, **365 (1549)**, 2019–2024,

Zuckerberg, B., W. F. Porter, and K. Corwin, 2009: The consistency and stability of abundance-occupancy relationships in large-scale population dynamics. *Journal of Animal Ecology*, **78 (1)**, 172–181,

6 Appendix S1. Occupancy model formulation

We implemented our spatio-temporal occupancy models using the 'stPGOcc' function in the spOccupancy package Doser et al. (2022) in the R Statistical Environment R Core Team (2024).

Explanation of subscripts used in the model:

$j = 1, ..., J$ (sites)

$t = 1, ..., T$ (years)

$k = 1, ..., K$ (surveys)

6.1 Occupancy sub-model (ecological process)

We formulated our occupancy model as

$$z_{j,t} \sim \text{Bernoulli}(\psi_{j,t})$$

$$\text{logit}(\psi_{j,t}) = \mathbf{x}_{j,t}\boldsymbol{\beta} + \omega_j + \eta_t$$

where $z_{j,t}$ represents the latent (unobserved) true occupancy state of site j in year t, $\psi_{j,t}$ is the probability of occupancy at site j in year t, $\boldsymbol{\beta}$ is a vector of coefficients for covariate effects (including an intercept) and $\mathbf{x}_{j,t}$ is a row-vector of the covariate values at site j in year t. ω_j and η_t are the multivariate normal spatial and temporal random effects.

Spatial random effects (ω_j) were estimated using a Nearest Neighbor Gaussian Process (NNGP) Datta et al. (2016); Finley et al. (2019); Doser et al. (2022), with an exponential covariance structure. In this model, the variance of the random effects is constant, σ^2, and the correlation between random effects at two sites at a distance d apart is $\exp(-\phi d)$, where the ϕ represents the rate at which the correlation decays. Thus, the distance at which the spatial autocorrelation falls below 0.05 is $-\log(0.05)/\phi \approx 3/\phi$, which may be interpreted as the spatial extent of the autocorrelation (used for selecting reasonable upper and lower bounds for the prior probability distribution of ϕ).

We modeled the temporal random effects (η_t) using an AR1 auto regressive structure. The covariance between two time points t_0 and t_1 is thus

$$\sigma_T^2 \rho^{|t_0 - t_1|}$$

where σ_T^2 is the temporal variance (magnitude) and ρ is the correlation between two successive years (one time unit).

In the final occupancy sub-model, the covariates included were latitude, year, elevation (represented by a cubic spline with 2 knots), and the three-way interaction between them.

6.2 Detection sub-model (observation process)

We formulated the detection model as

$$y_{j,t,k} \sim \text{Bernoulli}(p_{j,t,k} z_{j,t})$$

$$\text{logit}(p_{j,t,k}) = \mathbf{v}_{j,t,k} \boldsymbol{\alpha}$$

where $y_{j,t,k}$ is the detection/non-detection (1/0) observation at site j in year t and survey k. $p_{j,t,k}$ is the probability of observing a bluethroat, given that it is present, for site j in year t and survey k. $\boldsymbol{\alpha}$ is a vector of detection coefficients, and row vector $\mathbf{v}_{j,t,k}$ holds the covariate values at site j in year t and survey k.

In the detection sub-model, we estimated a separate intercept for each week, as well as including effort (the number of reports of background species in a given survey (*i.e.*, week), latitude, elevation, and the interaction between latitude and elevation as covariates.

7 Supplemental figures

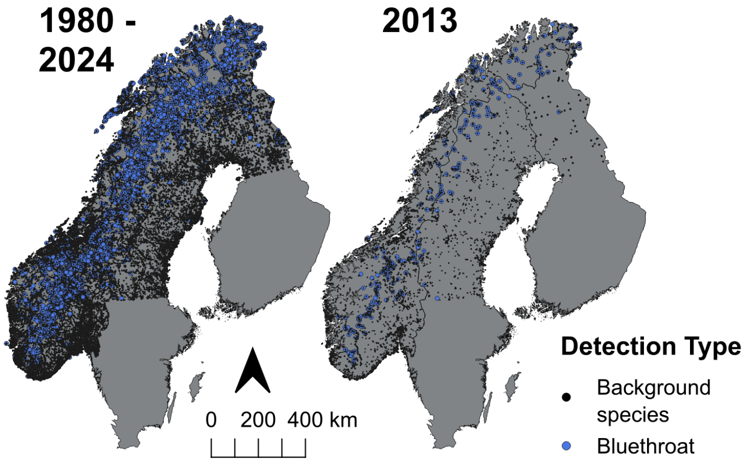

Figure S7: Maps showing reports of background species for the whole study period (left) and reports of bluethroats and background species for the middle year of the study (2013, right), as an example of the dataset.

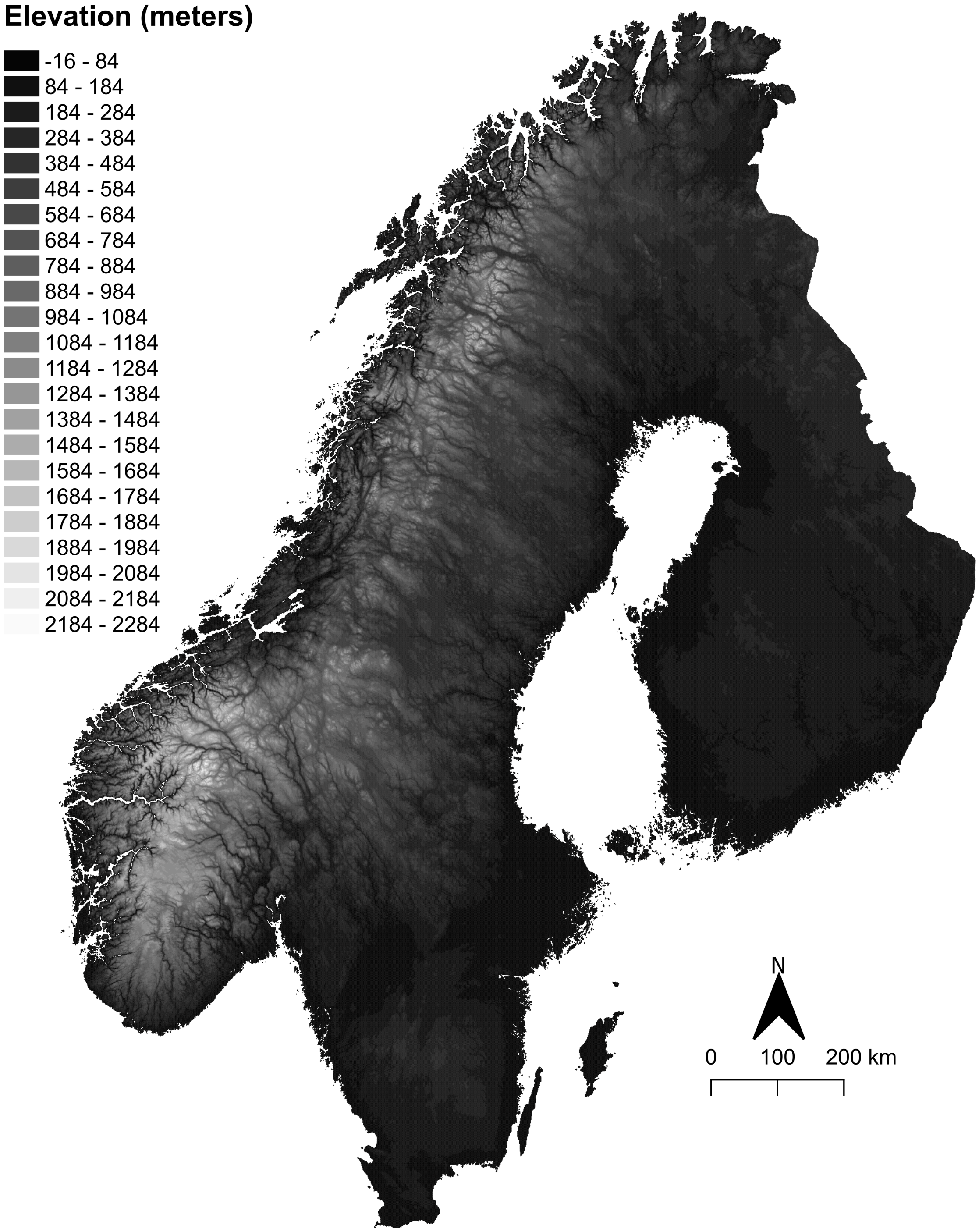

Figure S8: Map showing the mean elevation for each 1-km hexagonal grid cell in the Fennoscandian peninsula, derived from a 30-m global Digital Elevation Model with forests and buildings removed.

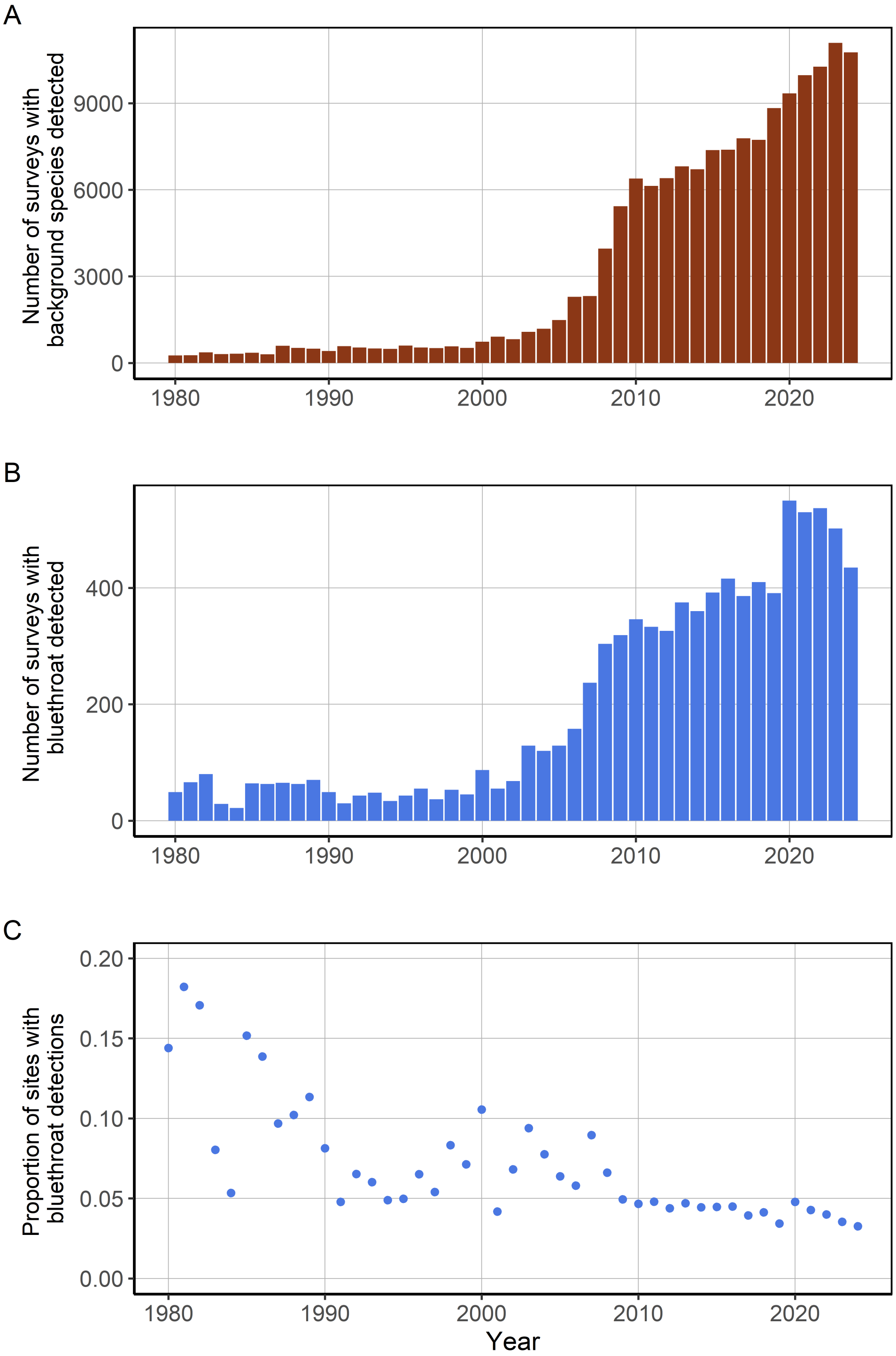

Figure S9: Visualization of the number of surveys each year across all sites. (A) shows the number of surveys where background species were detected (*i.e.* the number of sites surveyed), and (B) shows the number of surveys during which bluethroats were detected. (C) shows the naive proportion of sites that had bluethroat detections in each year of the study, calculated as the number of sites where bluethroats were detected at least once divided by the total number of sites surveyed in that year.

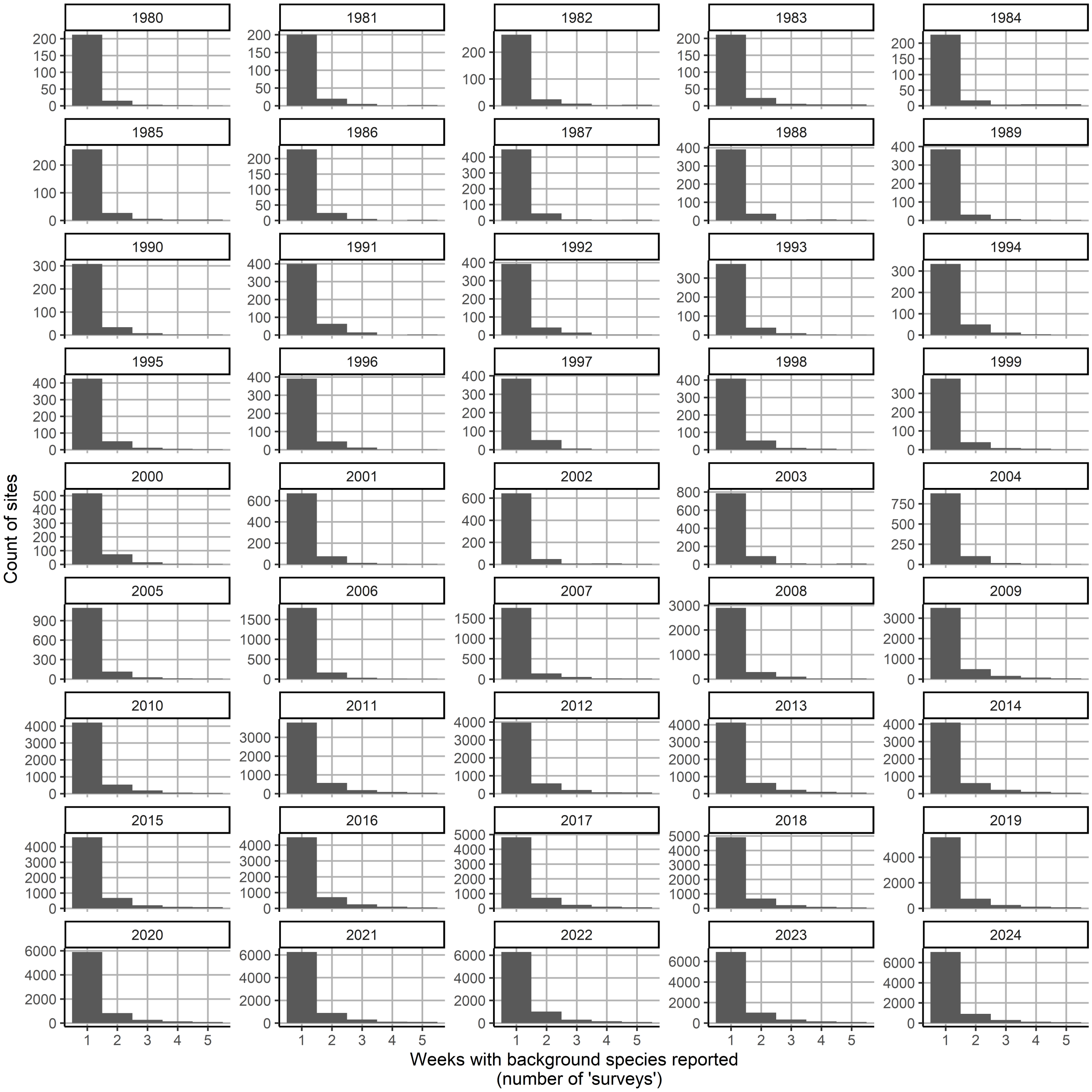

Figure S10: We used observations from one week (7 days) as a 'survey' in this study. This histogram shows the surveyed sites in each year and the number of sites with each number of surveys (1-5). Most surveyed sites had only one week with effort (*i.e.*, background species reported) in a given year, but some sites were surveyed multiple times allowing for estimation of detection probabilities. Our primary survey period was 10 June - 1 July (5 weeks), so the maximum number of surveys in a given year was 5.

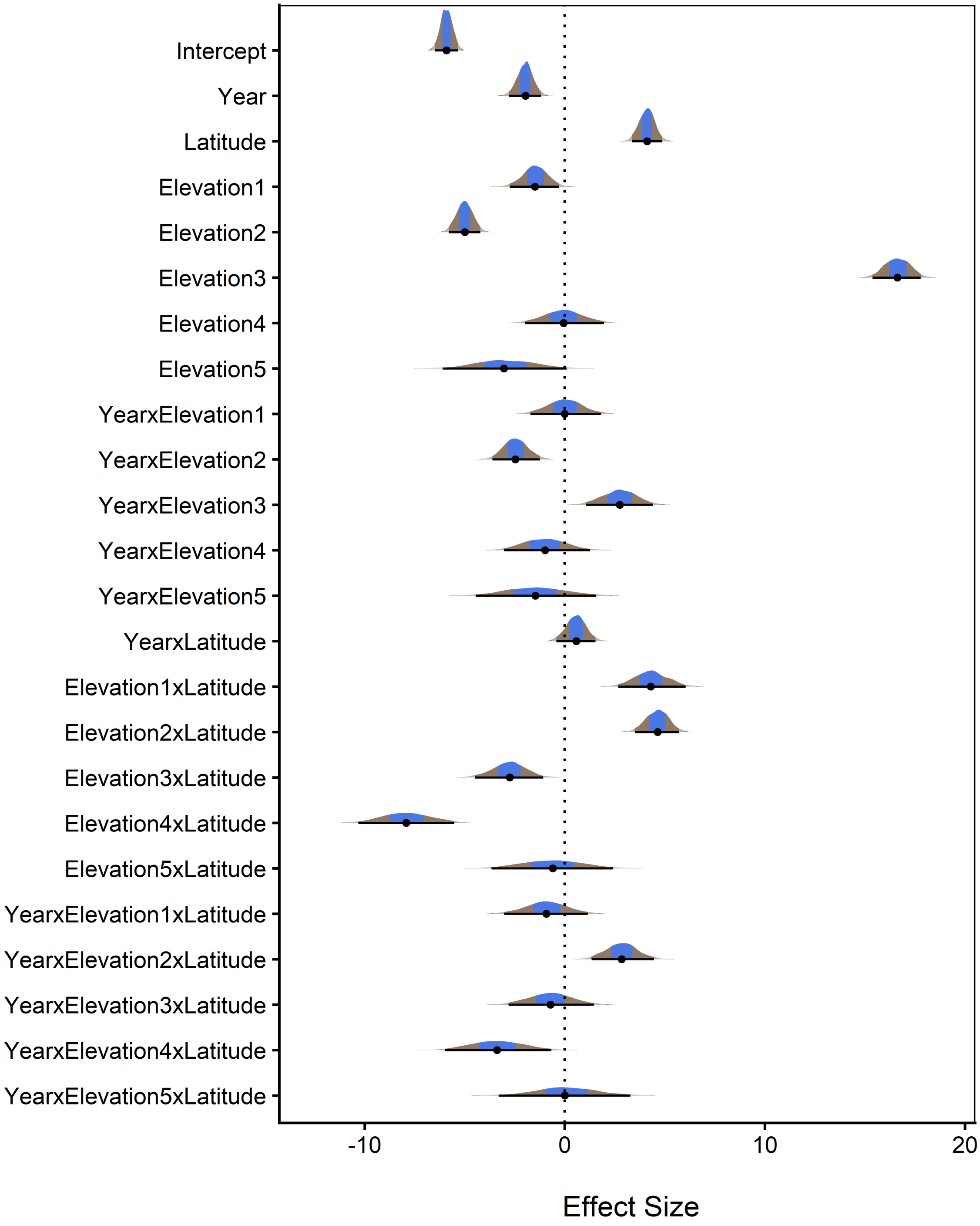

Figure S11: Full posterior distributions for all the occupancy covariate coefficients. The center blue section depicts the 50% credible interval, the darker brown represents the 95% credible interval, and the light brown represents the 99% credible interval. All predictor variables were standardized prior to model fitting by subtracting the mean and dividing by 2 standard deviations. Effect sizes are thus change in log-odds for occupancy per two standard deviations change in the predictor variable. The five elevation parameters represent the B-spline terms for the elevation portion of the model, but these terms do not have a specific interpretation individually.

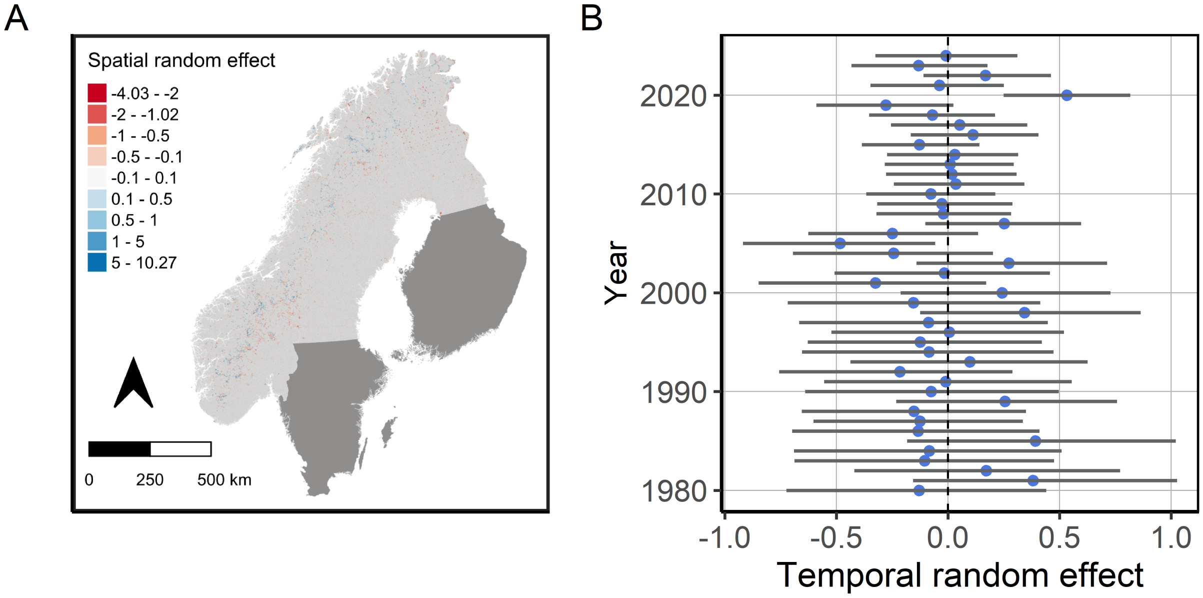

Figure S12: Plots of the (A) spatial and (B) temporal random effects and 95% CRI from the model output.