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Review Paper

Statistical models for the persistence of threatened birds using citizen science data: A systematic review

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ABSTRACT

Background: Due to risk factors such as climate change, habitat destruction, overhunting and pollution, bird extinctions are now occurring at a rate that far exceeds their speciation rate. There are no robust indicators of biodiversity conservation that can be used to complement existing national indicators of economic and social health. The statistical methods which are used to model and evaluate the persistence or extinction risk of threatened bird species using citizen science data are reviewed in this study. Citizen science data helps to increase the number of records, thereby improving our understanding of the dynamics in declining bird species populations.

Methods: Adhering to the PRISMA guidelines a comprehensive systematic review was performed using three databases: *ProQuest Central*, *Scopus* and *Web of Science* from January 1900 to January 2019. Only journal articles which analysed the persistence or extinction risk of threatened bird species using a statistical model, predictive model or a trend analysis, developed using citizen science data were included in this study. Bird species in near threatened or least concern categories that are declining in population/range were also included, since these may be the next wave of species to be added to the endangered species lists.

Results: Most of the 39 unique studies describing statistical models for this purpose used generalized linear models, followed by hierarchical/linear mixed models, machine learning models and persistence probability models respectively. A quality assessment tool was created in order to evaluate these articles. The review suggested several methods for measuring the persistence of threatened bird species, but there was no attempt to identify critical tipping points using methods such as change-point analysis.

Conclusion: The findings suggest that the persistence of threatened bird species varies depending on various risk factors which need to be addressed in order to produce better outcomes for the conservation of threatened birds. This review reveals the most suitable statistical methods for this purpose.

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1. Introduction

Birds play a vital role in ecosystems. The services they provide for the ecosystem basically fall into two categories which occur via behaviour such as consumption of agricultural pests and which occur via bird products such as nests and guano (Whelan et al., 2008). Birds can move nutrients from one place to another which is most important for plant growth and capable of stimulating primary productivity which means supports the functioning of ecosystems (Environmentalscience.org, 2019). When a bird species is lost, the benefits it might have afforded are gone forever. All of these benefits to humans and other organisms will likely decline along with bird numbers and species. Because birds can have an important role in controlling other organisms, their decline may even encourage the spread of disease (American Museum of Natural History, 2019).

Bird extinctions are now occurring at a rate that far exceeds their speciation rate due to risk factors such as climate change, habitat destruction, changes to wetlands and coastal environments, predation by feral predators, overhunting, toxic pollution and ecological change which are caused by natural or man-made influences. Each extinction diminishes the diversity and complexity of life on earth (Region 4 Southeast Region, 2019). The world's tropical forest bird population is estimated to be permanently reduced by 144 million individuals per year. From all known 9916 bird species, 129 are extinct, 1313 are threatened with extinction and 197 are considered critically endangered and are on the brink of extinction according to BirdLife International's assessment for the 2012 IUCN Red List (Butchart, 2013).

In a general sense a threatened bird species is one which is declining in abundance or occurrence and is headed towards extinction. There are different categories of threat for species based on the factors which are affecting them and the speed or extent of their decline. These threat categories are determined mainly by the International Union for Conservation of Nature (IUCN) (IUCN Red List of Threatened Species, 2019). Persistence of species has been defined as “the continued or prolonged existence of species”. The past decade has seen a resurgence of interest in extinction, yet research on this topic is still at a reconnaissance level, and the present understanding of its role in evolution is weak. There are no robust biodiversity conservation indicators that can be used to complement existing national indicators of economic and social health (Raup, 2018).

Citizen Science (CS) can directly contribute to biogeographical knowledge and conservation policies by increasing the number of recorded species in large geographic areas. The cost-effectiveness of CS data collection offers the potential for scientists to tackle research questions on large spatial and temporal scales (Aceves-Bueno et al., 2018). The Annual Report 2018-19 for the Port Phillip and Western Port Catchment Management Authority (Ppwcma.vic.gov.au, 2019) provides an example of the power of citizen science for monitoring the persistence of birdlife in the vicinity of Melbourne, Australia. Between the 2005-06 and 2016 analyses the number of wildlife sightings increased from 437,845 to over 3 million dues to a proliferation of citizen science survey programs (MacKenzie, 2018).

In this systematic review the statistical modelling techniques used to identify suitable factors to explain and measure persistence or extinction risk of threatened birds will be considered. Most of the studies have considered the risk factors of habitat destruction and climate change and all the studies have analysed citizen science databases or survey data while focusing on specific breeding and non-breeding seasons, or by predicting bird species behaviour adaptation.

However, in this systematic review we focus only on the journal articles that consider bird species identified by the IUCN red list assessment criteria, and the bird species that may be declining in population/range (in near threatened or least concern categories), as these may be the next wave of species to be added to the endangered species lists. These articles consider persistence or extinction risk measures, which are collected through citizen science data and used in some form of quantitative analysis using statistical modelling, predictive modelling or trend analysis to assess the persistence of threatened bird species.

It is expected that this review will help researchers to identify appropriate statistical models for evaluating persistence measures for identifying threatened bird species worldwide using citizen science data. Further, we hope that the findings of this systematic review will help to create more effective and efficient responses in the future for saving threatened bird species worldwide by statistically estimating the extinction risk and prioritizing the conservation of threatened bird species in the future.

2. Materials and methods

2.1. Literature search

The study considered evaluations of the persistence or extinction risk of threatened birds conducted using citizen science data. To find the relevant research articles, a systematic search of the literature was carried out using electronic databases: *Web of Science*, *Scopus* and *ProQuest Central*. This literature search was limited to English journal articles which were published from January 1900 to January 2019. The above databases all show an increasing trend in research focused on threatened bird species from 1990 onwards with increasing use of citizen science data. Only individualized keywords were used in the search strategy for the above-mentioned databases, in order to extract more relevant articles and also since these databases do not have a library indexed language. The following lists provide the series of keywords used for each database.

2.1.1. Web of Science

(TS=(“bird*”) AND TS=(“threatened” OR “endangered” or “vulnerable”) AND TS=(“citizen science”) AND TS=(“persistence” OR “extinction risk”) AND TS=(“statistic*” OR “statistical model*” OR quantitative OR “Models, Statistical” OR trend* OR “predictive model*”)) AND LANGUAGE: (English)

2.1.2. Scopus

("bird*") AND ("threatened" OR "endangered" OR "vulnerable") AND ("citizen science") AND ("persistence" OR "extinction risk") AND ("statistic*" OR "statistical model*" OR "Models, Statistical" OR "trend*" OR "predictive model*") AND (LIMIT-TO (SRCTYPE, "j")) AND (LIMIT TO (LANGUAGE, "English"))

2.1.3. ProQuest Central

((bird*) AND ((threatened) OR (endangered) OR (vulnerable)) AND (citizen science) AND ((persistence) OR (extinction risk)) AND ((statistic*) OR (statistical model*) OR (Models, Statistical) OR (trend*) OR (predictive model*))) AND la.exact("ENG") AND PEER(yes) AND stype.exact("Scholarly Journals")

2.2. Inclusion and exclusion criteria

To select articles better matched to the objective of this systematic review, four main inclusion criteria were developed. Articles were selected if (i) the study focused on threatened bird species classified under IUCN red list assessment criteria, and, for bird species in near threatened or least concern categories that are declining in population/range; (ii) Citizen Science data were used to conduct the study; (iii) the study discussed persistence or extinction risk of threatened bird species; (iv) the study carried out a quantitative analysis using statistical modelling or predictive modelling or trend analysis.

2.3. Selection process

The review was conducted in three steps. Firstly, the first Author title-screened all articles for potential inclusion. Then the other two authors were given online access to view the results. The abstracts of those studies were then independently reviewed by the first two authors and shortlisted the most relevant articles. In the final step, the accepted articles by both reviewers were retained and the questionable articles were directed to the third reviewer for resolution.

2.4. Data extraction

The initial database search was able to identify a total of 2336 articles which included 2158 articles from ProQuest Central, 177 articles from Scopus and 1 article from Web of Science. A manual search using a snowball sampling technique using paper references added 23 articles. These articles were uploaded to EndNote software and 87 duplicates were removed by the first author. This process shortlisted 57 articles for a full-text review, out of which the team agreed on 39 unique articles for inclusion in this review. The PRISMA flow diagram (Fig. 1) outlines the above search and review process.

2.5. Quality assessment

There is no consensus on the best way to assess study quality (quality assessment checklist) of ecology papers. Most common issues in papers are appropriateness of study design for the research objective, risk of bias, choice of outcome measure, statistical issues, quality of reporting and generalisability. In order to determine the good quality papers with minimal issues, a new checklist named "Udani DM Checklist" was created, referring to the "Downs and Black checklist" (Black, 1998). This checklist consists of 22 items distributed among five sub scales, namely; reporting (9 items), external validity (4 items), internal validity - bias (4 items), internal validity - confounding (4 items) and power (1 item). The performance of the quality assessment items is assessed using "1" for compliance and "0" for non-compliance. The standard deviation for each item is calculated as a check of the discrimination capability for each item. The maximum score that a study can obtain is 22, with higher scores indicating better quality. In this review the Udani DM scores have been categorized as follows; low quality (10–12), average quality (13–15), good quality (16–18) and excellent quality (19–20). Appendix 2 shows the 22 questions included in "Udani DM Checklist".

2.6. Registration and protocol

This systematic review was designed and reported according to the Preferred Reporting Items for Systematic Review and Meta-Analysis Protocols (PRISMA-P) guidelines (Moher et al., 2015) and Fig. 1 shows the overall search strategy in broad terms. The protocol for this review has been published in protocols.io and osf.io in order to enhance the reproducibility of the results. The protocol can be accessed from https://doi.org/10.17504/protocols.io.3dagi2e and https://doi.org/10.17605/OSF.IO/6VGUK respectively.

2.7. Taxonomy for journal articles

There are many different statistical techniques that can be used to model bird persistence measures using citizen science data. The "Guide for choosing among statistical techniques" published in Tabachnick and Fidell (2013) has been used to classify the various statistical techniques found in the shortlisted articles. These articles have also been classified in terms of the type of citizen science data used, the type of persistence models used, and the nature of the risk factors identified.

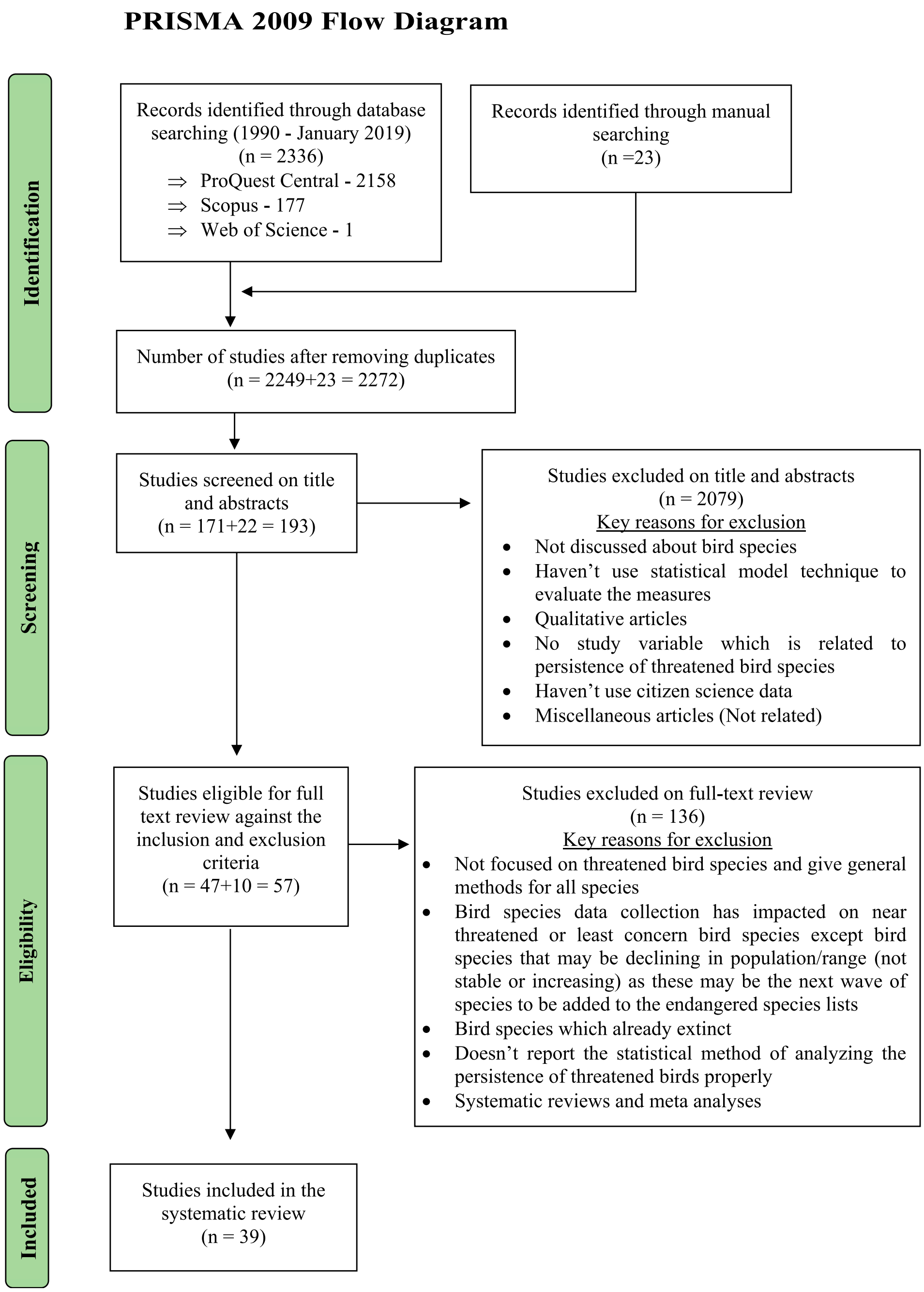

Fig. 1. PRISMA flow diagram.

3. Results

This review refers to 39 studies conducted between 1947 and 2019 in 10 different countries, with more than one country providing the data for some of the articles (Boakes et al., 2018; Wilson et al., 2013; Studds et al., 2017). The highest number of studies was carried out in the United States of America (12) and Africa (7), followed by the East Asian–Australasian Flyway (3), Canada (3), Australia (2). Due to the variability in the included studies in terms of study design, sample size, persistence or extinction risk factors, objectives and statistical methods for analysing the data, this systematic review will provide only a qualitative review, rather than a meta-analysis.

Approximately half (46%) of the studies considered only a single bird species; for example, Carnaby's cockatoo (*Calyptorhynchus latirostris*), Aransas-Wood Buffalo Whooping cranes (*Grus americana*), Western Grebes (*Aechmophorus* *occidentalis*), Black Harrier (*Circus maurus*), Western capercaillie (*Tetrao urogallus*). Group studies of species were used for the remaining studies; for example, forest pigeons, North American quails, breeding species of Chinese protected birds.

3.1. Statistical methods

In these 39 papers, citizen science data were analysed using more than 10 different statistical models and these models can be assigned to one of four categories. Generalized linear models (41%), including general linear models, generalized additive models, Poisson regression models, ANOVA, logistic regression models and least squares regression models (Amar and Cloete, 2017; Aubry et al., 2016; Carvalho et al., 2014; Dhanjal-Adams et al., 2019; Downs et al., 2014; Erickson et al., 2014, 2017; Kamp et al., 2009; Lee et al., 2017; Pearse et al., 2018; Pryke et al., 2010; Williams et al., 2017; Wootton and Bell, 2014; Xu et al., 2019; Yong et al., 2017). Next came hierarchical/linear mixed models (31%), including hierarchical Bayesian models, hierarchical Poisson regression models, hierarchical linear regression models, general linear mixed models and mixed effects cumulative logit regression models (Berry et al., 2010; Boakes et al., 2018; Clemens et al., 2016; Culp et al., 2017; Garcia-Heras et al., 2019; Kalle et al., 2018; Rushing et al., 2015; Studds et al., 2017; Thogmartin et al., 2004; Ward et al., 2015; Wilson et al., 2013, 2018). Next most preferred models were machine learning models (23%), including predictive models, maximum entropy models, boosted regression trees (BRT), random forests (RF) and clustering models (Hart et al., 2018; KrÓLikowska et al., 2017; Li et al., 2015; Ramesh et al., 2017; Rösner et al., 2014; Runge et al., 2015; Shaw et al., 2015; Tanner et al., 2017; Wogan, 2016; Zlonis et al., 2017). The final category consisted of persistence probability models (5%) (Collen et al., 2010; Butchart et al., 2018). Out of these 39 papers only one paper used a combination of the above categories, namely generalized linear and machine learning models (Shaw et al., 2015). Since this paper mostly used machine learning techniques, it is included with the machine learning models. Appendix 1 summarizes the information extracted from the shortlisted articles.

Akaike's Information Criterion (AIC) and Area Under Curve (AUC) were used to identify the best model in 43% of analyses with Monte Chain Monte Carlo (MCMC) estimations. The majority of statistical analyses were conducted using R software, followed by JAGS in a Gibbs-sampling environment, and MATLAB. All the machine learning models were generated using Maxent software with only one exception (Ramesh et al., 2017). Maxent software is used for the modelling of species spatial distributions on the basis of a set of environmental or climate layers, together with a set of sample locations where the species of interest have been observed. This tool compares well with or outperforms other modelling techniques for this purpose, and the results have been shown to be similar to those obtained from more conventional regression-based approaches used for modelling environmental correlates. Maxent can be applied to address a variety of ecological questions depending on how the models are calibrated and evaluated.

3.2. Citizen science data

All the studies used observational data collection designs with 49% of the studies conducted using citizen science databases such as; eBird, BirdLife Australia, Southern African Bird Atlas Projects (SABAP 1 and 2) and Christmas Bird Count Data. These databases are populated with the sightings of birds provided by citizens outside of any formal survey paradigm. The remaining 51% of studies were conducted using citizen science survey data collected in protected areas, forests, country-side or urban areas. Survey data were collected using several methods such as; opportunistic sighting and telemetry data (Pearse et al., 2018), sightings marked with GPS-GSM or PTT tracker devices (Garcia-Heras et al., 2019), fresh capercaillie droppings (Rösner et al., 2014), stable hydrogen isotopes (Rushing et al., 2015), pitfall trapping (Pryke et al., 2010) etc. Researchers considered important factors affecting species trends such as breeding or non-breeding season, climate suitability, age and sex, seasonal changes and human population density near the area where the data were collected.

There are two types of data collected for these studies. First type is called abundance data which tracks the total population size, usually measured as the number of individuals found per sample (Joseph et al., 2006). The other type is called occurrence data which consist of less information-rich data such as detection/non-detection (presence/absence data) without counts. The occurrence indicates that a site is occupied which means the local abundance is greater than zero (Kery et al., 2013). Both types of data are related to a particular time and place. The majority of the studies (82%) used occurrence data for their analysis whereas 18% of the studies used abundance data.

Out of these 39 papers, 54% of the studies discussed the biases present in citizen science data and some studies clearly stated how they overcame those issues (Kosmala et al., 2016). In these papers, they have discussed the following biases.

- Any count-based evaluation of a model is likely to indicate under-estimation, due to undercounting of birds in the wild. The extent of undercounting was not estimated for any of the data sets. This bias is accommodated using statistical models such as Hierarchical Bayesian occupancy-detection (BOD), and machine learning models adapted for some forms of undercounting using Maxent software. Prior distributions ensure that actual population sizes are reflected in final estimates.
- Most of the data were opportunistically collected, presence-only data (as opposed to systematic survey count data), and there were likely to be many pseudoabsences where a species was present but not recorded. In addition, other spatial and temporal biases due to more comprehensive reporting of threatened birds in protected areas, were expected. Pseudoabsence locations were therefore randomly generated for addressing potential bias in survey data, using sighting

locations from previous and current years to account for pseudo-absences, in order to ensure that "background" locations are likely to contain the same biases as the sighting data.
- To accommodate birds that migrate to a location only in a breeding or a non-breeding season, average counts were obtained across an appropriate number of years in order to provide an unbiased estimate of population numbers.
- Only experienced observers were used to conduct surveys, and surveys were designed to minimize under-reporting, overlooking or double counting.
- Volunteer observers are re-trained annually and there are ongoing validation studies to quantify biases such as species misidentification. In addition, observers are often changed from one survey to the next in order to reduce bias associated with observer skill and species detection history.
- Median counts derived from various datasets in overlapping years are used to accommodate potential biases in opportunistic sightings.

3.3. Risk factors

In this review, risk factors that may influence the persistence of threatened bird species were categorized as biotic and abiotic. The biotic risk factors include habitat loss, climate change, prey availability, long migration distance and predation. The abiotic risk factors are attributed to human influence factors such as hunting, agriculture intensification, land use change, additional recreational activities, illegal pet trade and high collision mortality on power lines. Habitat loss was the most commonly cited risk factor (34%), followed by abiotic risk factors (25%) and climate change (22%).

Table 1 shows a summary of the statistical methods grouped under categories for citizen science, type of data and risk factors. Out of these 39 papers 36 also discussed the conservation efforts being made to protect threatened bird species.

3.4. Quality assessment

A quality assessment was carried out for all the 39 studies using the Udani DM quality assessment tool. The quality scores ranged between 10 and 20 with a mean score of 16. Two studies were categorized as low quality (10–12), 14 studies were categorized as average quality (13–15), 20 studies were categorized as good quality (16–18), and 3 studies as excellent quality (19–20). As indicated by their standard deviations, "Are the occurrence details (location/time) provided for all bird species considered? (A list of studied bird species is provided)", "Have actual probability values been reported (e.g. 0.045 rather than <0.05) for the main outcomes except where the probability value is less than 0.001?", "Were the data obtained from a reputable source which validates data appropriately?" and "For comparative studies was the data collection effort, duration and area the same/similar?", are the best items to discriminate between articles in terms of quality.

3.5. Limitations

A meta-analysis has not been performed due to the wide range of statistical methods applied and the wide range of research objectives and species studied. Hurdle models were not included in this review (Arab, 2015; Sarul, 2015).

4. Discussion

In this review we identified four main categories of statistical approaches for describing persistence data obtained through citizen science; namely general linear models used for cross-sectional studies, machine learning models used for large distributional studies, hierarchical/linear mixed models used for spatial and temporal multi-level studies and persistence probability models used for time stochastic studies. The most popular method of analysis is generalized linear models followed by hierarchical/linear mixed models. Machine learning models are the third most preferred method followed by persistence probability models.

Table 1
Categorization of research articles.

Category		Methods (#)				Total
		GLM	MLM	HLMM	PPM	
Citizen science	Database data	7	6	5	1	**19**
	Survey data	9	3	7	1	**20**
Type of data	Abundance data	4	0	3	0	**7**
	Occurrence data (Presence-absence data)	12	9	9	2	**32**
Risk factors (*)	Biotic	20	13	15	2	**50**
	Abiotic	12	3	11	1	**27**

* Total number of risk factors mentioned.
# GLM: Generalized Linear Models, MLM: Machine Learning Methods, HLMM: Hierarchical/Linear Mixed Models, PPM: Persistence Probability Models.

Generalized linear models were often used to test for changes in occurrence over time or to evaluate population trends and also used to determine the effects of habitat covariates for the abundance of bird species. All the hierarchical models assumed over-dispersed Poisson distributions for counts, and the models were fitted using Markov Chain Monte Carlo methods. Hierarchical models used over-dispersed Poisson distributions without considering the over-dispersion since this Bayesian approach provides robust solutions for count models. But some studies used a Negative Binomial distribution instead of Poisson in order to address the over-dispersion issue. Hierarchical Bayesian approaches were used in all cases because they provide a robust framework to account for sources of variation at multiple scales including observer effects, overdispersion effects and the spatially specific effects of drought across species range (Thogmartin et al., 2004). Linear mixed models were commonly used to quantify the effects of the predictors. Machine learning models such as maximum entropy models were used to test which variable selection approaches performed best for creating ecological niche models, and predictive models were used to predict the distribution of each species from the species count data sets. All these machine learning models were fitted using Maxent software. Persistence Probability models were used to estimate the time dependence for the probabilities of extinction of rare species.

Annual data was used to analyse migratory bird species and monthly data was used for non-migratory or local bird species. Some studies conducted research to determine the behavioural patterns in breeding and non-breeding seasons which influence the long-distance dispersal of migratory birds. Fixed effects such as age and sex, breeding/non-breeding habitat quality, population size, climate change (rainfall, temperature, snowfall) were used to examine the abundance or occurrence of bird species. Random effects such as year, month were used to test the significance of the fixed effects. Standardization of predictors was used to address multicollinearity between the predictors.

All the studies included in this review are observational with citizen scientists providing abundance or occurrence data for threatened bird species, mostly using survey data. Modern technology is providing many exciting new methods for collecting this survey data. For survey data most of the studies used occurrence data rather than abundance data. Counts provided by citizen science data can be regarded as indicative of population size and can be used to estimate spatial and temporal patterns in relative population abundance (Link and Sauer, 1998). Citizen science databases including eBird, BirdLife Australia, Southern African Bird Atlas Projects (SABAP 1 and 2) and Christmas Bird Count Data were collected by private individuals. The accuracy of citizen science data varies depending on volunteer experience. Data produced through citizen science may contain error and bias and this can be mitigated using statistical tools. However, many of the systematic biases in citizen-science data are the same biases that occur in professionally collected data such as; spatially and temporally non-random observations, non-standardized capture or search effort, under-detection of organisms, confusion between similar-looking species and the over or under-reporting of rare, cryptic, or elusive species as compared to more common ones. The only known bias specific to citizen science is the potentially high variability in terms of image quality and location accuracy. Expert scrutiny of images provided, standardization of measurement tools, collection of instrument calibration data, and collection of multiple independent volunteer measurements, can be used to improve the quality of citizen science data (Kamp et al., 2009).

The analysis of risk factors indicates that many species have experienced range contractions due to biotic risk factors, including habitat loss, climate change, prey-availability, long migration distance and predation. In addition, abiotic risk factors including hunting, agriculture intensification, incremental recreational activities, land use change, illegal pet trade and high collision mortality on power lines have been identified as risk factors. While quantifying these risk factors the studies also considered other factors such as; breeding and non-breeding habitat quality, age and sex, human population density near the species area, the estimated size of the area, the latitude and longitude of each site. Environmental data such as rainfall, temperature, snow cover and mapping data were obtained using databases such as WorldClim and the NOAA Earth System Research Laboratory. Some of the studies generated predictive habitat maps (ecological niche modelling) from bioclimatic, topographic and land-use variables, allowing the examination of trends in species' distribution using Maxent software (Berry et al., 2010).

As a general rule in ecology, occupancy is correlated with abundance (Andrewartha and Birch, 1954) which means that occupancy surveys can be used to predict abundance for a variety of applications. However, in the context of a threatened species, it is important to examine occupancy and abundance separately, because a high probability of persistence might be the result of a historically large bird species colony rather than a reflection of current abundance.

The actions needed to help save most threatened species are often not clear and for many species research is required to enhance recovery efforts. The most urgent actions needed to protect and effectively manage important bird and biodiversity areas, to control or eradicate invasive alien species, restore habitat, control hunting, raise awareness, and, in some cases, establish captive breeding and reintroduction programmes. There is good evidence that such actions can bring species back from the brink of extinction, with a suite of species that were once reduced to tiny populations now well on the road to recovery (Butchart, 2013).

Extinction risk estimates provide a foundation for prioritizing conservation actions for endangered species (Runge et al., 2015). Geographic range size is important for measuring extinction risk for all recognized taxa used by the International Union for Conservation of Nature (IUCN). Considering sub-criteria such as habitat quality, the number of mature individuals, the extent of the decline in quality of habitat and degree of fragmentation of habitat among other variables, threat status is categorized as Vulnerable, Endangered and Critically Endangered. Species need conservation actions mainly when they have experienced distribution-wide declines in recent decades. These species need urgent conservation actions such as population estimation, habitat fragmentation analysis, and landscape management (Ramesh et al., 2017).

Conservation planning activities generally require knowing what and where habitats need to be protected in order for bird species populations to be sustainable. Population monitoring is therefore key to the effective conservation of threatened species. Because species' range and distribution analysis allow the evaluation of impacts and responses to risk factors such as climate change and land use, statistical modelling has an important role to play in conservation. These models are important for the identification and determination of exposure levels of potential threats for individual species and for predicting changes in extinction risk. Studies examining life history traits are also needed for species that are of high conservation concern and experiencing elevated rates of extinction. The capability to model and map abundances of high priority threatened bird species over large regions is therefore critical for the identification and prioritizing of habitats for conservation action and for future monitoring.

5. Conclusions

Large, spatial data sets with long time series are rare, even for birds, and crucial for studying the role of risk factors in driving shifts in species ranges, egg laying and migratory timing. In summary, this systematic review was able to identify four main classes of statistical modelling methods that have been used to describe the persistence of endangered birds using data obtained from citizen science databases and surveys. They are generalized linear models, hierarchical/linear mixed models, machine learning models and persistence probability models.

Most of the studies have used generalized linear models to analyse threatened bird species abundance. The predictors of persistence for threatened birds are best analysed using GLMs or mixed models. Persistence Probability models are best used to identify extinction risk rather than giving reasons for persistence.

Contrary to expectation no studies with change point analysis to analyse species counts using citizen science data were found. In order to detect changes in persistence risk quickly, change point models hold particular promise for triggering conservation effort before species are even identified as being endangered or threatened. The increasing availability of good quality citizen science data will allow the use of these and other data intensive models to ensure that conservation initiatives are better supported in the future.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.gecco.2019.e00821.

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