**Risk-based viable population monitoring from community science data**

**Rapid assessment of local persistence from population trends with community science data**

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**1 | INTRODUCTION**

“*The science of ecology is the study of distribution and* ***abundance***.” Nicholas J. Gotelli (2008)

Understanding changes in species abundances (i.e. population dynamics) is a quintessential ecological topic to inform conservation actions (Callaghan et al., 2024; Dennis et al., 1991; Staples et al., 2005). However, long-term and large-scale structured monitoring data is rare (Robinson et al., 2021), leading to uncertainty of population dynamics for most biodiversity on the planet (Lees et al., 2022; Neate-Clegg et al., 2020). Different methods have been proposed to estimate abundance (Dénes et al., 2015), its rate of change (Bart et al., 2003; Fink, Johnston, et al., 2023), and thus inferring population dynamics to inform conservation (Staples et al., 2005). For example, a hierarchical Bayesian model was used to report the net loss of ~3 billion birds during the last five decades in the continental North America, combining monitoring data from long-term breeding counts and whether radars for resident and migrant species (Rosenberg et al., 2019). New source of data integrated to robust quantitative methods are promising approaches to complement rigorous monitoring efforts (Zhao et al., 2024).

Standardized long-term monitoring is essential to understand population dynamics (Blake & Loiselle, 2024; Neate‐Clegg et al., 2021), being the basic ingredient to robust methods in conservation. For example, population viability analysis aims to understand what has happened with the monitored populations after long-term monitoring. Despite its wide use, it has been suggested that conservation ecologists could ask rather how the population’s status is changing during the monitoring program, for instance by assessing the risk of decline below a prespecified threshold (Staples et al., 2005). Within short periods, the dynamic of the population monitored might be assessed from the complement of the risk of decline (), which we define here as the local persistence probability (). An important conundrum is that two simultaneous but independent sources of variation occur during population dynamic assessment: the ecological and the observational processes (Dénes et al., 2015; Dennis et al., 2006; Humbert et al., 2009). Account for these two processes will provide more realistic estimations of population trends from different monitoring initiatives.

Population dynamic assesment is complex, requiring the inclusion of mathematical models in the ecological (state) and observational (sampling) processes. The ecological process can follow deterministic models like textbook examples of exponential or logistic growth (Gotelli, 2008). Unfortunately, most populations do not respond to simple deterministic models, requiring modeling the ecological underlying process with the inclusion of demographic and/or environmental stochasticity (Evans et al., 2023; Fink, Johnston, et al., 2023; Humbert et al., 2009). This “process noise” works independently of the observation process, also named the “observation error” when detection is imperfect (Dénes et al., 2015; Dennis et al., 2006). Different hierarchical models could integrate these population processes. For example, by using “state-space” models on time-series observational data, ecologists can estimate the latent values of the population abundance time-series (Auger‐Méthé et al., 2021; Dennis et al., 2006; Evans et al., 2023). True abundance estimations under state-space models can assess independent population parameters like the growth rate, density dependence (when present), as well as stochastic “process noise” and “observation error” (Dennis et al., 2006; Dennis & Ponciano, 2014; Humbert et al., 2009; Ponciano et al., 2009). These estimated parameters provide robust assessment of population dynamics, which in turn serves to understand changes of the populations status through time by estimating local persistence probability (see Section 2.2) (Staples et al., 2005).

Time-series abundance data following discrete and equal sampling can be fitted with the Gompertz State-Space (GSS) population model (Dennis et al., 2006; Dennis & Ponciano, 2014). This model is a practical way to include density dependence, stochastic process variation, and stochastic observational variation with realistic dynamics of animal populations (Dennis et al., 2006; Evans et al., 2023; Taper et al., 2008). Although incorporating replicated sampling into the GSS model improves parameter estimation for population dynamics (Dennis et al., 2010), this improvement in repeated sampling methods still requires equal sampling in discrete time-series data. Special cases of GSS for unequal sampling include continuous-time density-independent Exponential Growth (or decay) State Space (EGSS) model and density-dependent Ornstein-Uhlenbeck State-Space (OUSS) model (see Section 2.1). In practice, the EGSS model simultaneously includes approaches of traditional log-linear regression of counts against time and Brownian motion diffusion processes (Humbert et al., 2009); the first approach assumes that variability in the data occurs only by the observation error noise, while the second approach assumes that populations are censured (without observation error) and variability in the abundance data occurs only by growth rate fluctuations from environmental variability, or ecological process noise (Dennis et al., 1991; Humbert et al., 2009). Similarly, the OUSS allows ecologists to estimate strength of density dependence, process noise, and observation error in data that includes, for example, gaps in sampling observations (Dennis & Ponciano, 2014). This kind of unequal sampling with gaps and observation error is usual in biodiversity monitoring initiatives that involve volunteer participation during data collection, defined as community science data.

Community science initiatives (also known as citizen or participative science) involve monitoring by volunteer participation mainly for collecting or reviewing data, becoming an increasing source of biodiversity information worldwide (Amano et al., 2016). Despite its contribution to biodiversity information, community science initiatives range in nature, with a trade-off between broad participation and including clear objectives, research design, and rigorous protocols during sampling events; this is evident between the unstructured and structured community science initiatives (Kelling et al., 2019). For example, iNaturalist ([www.inaturalist.org](http://www.inaturalist.org)) is a flexible global platform that incites massive participation of the public to submit incidence occurrence data (Di Cecco et al., 2021) or identify records (Campbell et al., 2023); this initiative has not constraint on spatial (where), time (when), or taxonomy (what) of the records, albeit absence of sampling event effort information besides the observer or identifiers (whom). In contrast, the North American Breeding Bird Survey is an example of a structured community science data, following a rigorous protocol by only highly skilled volunteers for monitoring bird populations in continental North America (Ziolkowski et al., 2023). Semi-structured approaches, somewhere in the middle of this spectrum, provide robust information for biodiversity monitoring while including essential details of the observation process (Kelling et al., 2019). From the semi-structured approaches, eBird is perhaps the most popular for analyzing bird records (Johnston et al., 2021; Kelling et al., 2019; Sullivan et al., 2014), including estimates of species status and trends. The current estimates of population dynamics from eBird strictly control for the observation process variability and other confounding environmental factors that affect species detectability or its relationship with the landscape (Fink, Auer, et al., 2023; Johnston et al., 2018). Despite its informative use, these “status and trends” are yet not available for all species in eBird and fit discrete-time stochastic exponential models as the underlying ecological process of the number of individuals reported and analyzed (Fink, Johnston, et al., 2023).

We aim to provide a rapid assessment of short trends of local persistence probability () by incorporating population dynamics robust models (Dennis & Ponciano, 2014; Humbert et al., 2009) withing the risk-based population viability monitoring framework (Staples et al., 2005) using time series data from eBird. We begin by organizing eBird data records in a time series of weekly high counts estimates, filtering by best practices for bias reduction (Backstrom et al., 2024; Johnston et al., 2021; Kelling et al., 2019; Strimas-Mackey et al., 2023). We selected a species with long-term monitoring efforts that varies in population dynamics in space, including recent expansions of its breeding ranges (Machado-Stredel et al., 2024; Poli et al., 2020). This example species provides benchmark population trends and seasonal dynamics; here, we focused on the new northern limit of the breeding range since 2018. Then, we estimated the local persistence probability for every week since 2020 by simulating trajectories of the population for a period of 2-years (104 weeks). In every week point of abundance estimation, we updated the model fitted, the estimated parameters of the population models for projected trajectories, and the probability to persist above a preestablished threshold after 2 years of stochastic dynamic. We provide an annotated program in R of our approach that could be adjusted and applicable to other species and locations (link code for peer review attached).

**2 | METHODS**

To conduct our analysis, we used the R software v4.3.3 (R Core Team, 2024). Specifically, we filtered the eBird data with the packages *auk* (Strimas-Mackey et al., 2018) and *tidyverse* (Wickham et al., 2019); we generated the hexagonal grid with the package *dggridR* (Barnes, 2023) as suggested in Strimas-Mackey et al. (2023); and we adjusted the R programs published by Humbert et al. (2009) and Dennis & Ponciano (2014), which require the package *MASS* (Venables & Ripley, 2002). In addition to figures using basic R or *ggplot2* (Wickham, 2016) within *tidyverse* (Wickham et al., 2019), we used the package *maps* (Becker et al., 2022) and *gridExtra* (Auguie, 2017) to load maps and generate composite figures. Code is available in FigShare (link available as accepted – code for peer review attached).

**2.1 | The state-space models**

We used two state-space models that are special cases of the discrete-time GSS (Dennis et al., 2006). The ecological process in the GSS model for (latent unobserved abundance population) is defined as , where and are constants representing population growth rate and density dependence, and is the environmental stochasticity or process noise; (Dennis et al., 2006). On the logarithmic scale (), the GSS becomes linear and follows an autoregressive model of order 1: , where , and is a constant that represents the strength of density dependence (Dennis et al., 2006; Ponciano et al., 2018).

The probability distribution of this logarithmic abundance is normal, with mean and variance changing as a function of time. However, if the strength of density dependence () ranges in absolute values (), the long-run probability distribution of log-abundance approaches a time-independent normal stationary distribution (), with mean and variance . Note that if (which means ), the discrete-time model follows density-independence and becomes (Dennis et al., 1991). In these state-space models, the estimated or observed log-abundance sampled arose from the unobserved state time-series and the observation error, ; .

The GSS population model incorporates these principles and has four unknown parameters under stationary distribution: , , , and (Dennis et al., 2006). However, if the observation data commenced before the assumed stationary distribution mean, the initial population become an additional unknown parameter. In case the initial population is known, as in translocation experiments, the observed data for initial population is the same realization of the latent variable () and could be treated as a known parameter (Dennis et al., 2006; Dennis & Ponciano, 2014). During such transition growth dynamics the density independent EGSS, without an equilibrium and the additional parameter of the initial population, seems more accurate to represent the trend of the population (Dennis et al., 1991, 2006; Humbert et al., 2009). Finally, be aware that the density-dependent stochastic GSS model does not include the deterministic “carrying capacity”, but a stationary distribution mean representing a long-term expected population size where the population fluctuates with some variation (Dennis et al., 2006).

The logarithmic transformation in the GSS discrete model opens the opportunity for estimating the infinitesimal mean and variance under a diffusion process for unequal sampling, Brownian motion diffusion in EGSS (Humbert et al., 2009) and Ornstein-Uhlenbeck diffusion in the OUSS population model (Dennis & Ponciano, 2014). In the next two subsections, we summarize each model, but specific statistical properties can be found elsewhere (Dennis et al., 1991, 2006; Dennis & Ponciano, 2014; Humbert et al., 2009; Taper et al., 2008).

**2.2.1 | Exponential Growth State-Space (EGSS)**

Let begin with the first model in most population ecology classes, the exponential growth, which could serve as a null hypothesis of density dependence models (Dennis et al., 2006). The exponential stochastic process for could be defined as , where defines the finite rate of change (; being the instantaneous rate of change), is the initial population (), and is the environmental stochasticity or process noise at time , which follows a normal distribution with mean and variance (). On the logarithmic scale (), the discrete-time process can be defined as a continuous diffusion process with the stochastic differential equation , where is a random perturbation representing the environmental stochasticity at the Itô log-transformation, or the intensity of noise scaled by , with (Humbert et al., 2009). The EGSS model includes a component in sampling times not equally spaced between times and (), and the log-abundance observed is defined as , where is the observation error and follows a normal distribution with mean and variance (). This model has four unknown parameters: (the trend parameter under density independence; note the notation differs from Humbert et al. 2009), (variability of process noise), (variability of sampling), and (the initial log-abundance population).

**2.2.2 | Ornstein-Uhlenbeck State-Space (OUSS)**

The OUSS model adds also a component in sampling times not equally spaced , where the observation error keeps a normal distribution and the same unknown parameter (), and the underlying unobserved population follows a continuous-time version of the GSS model. With the strength of density dependence parameter () ranging positive values (), the dynamic of the population is stationary. The relationship between parameters from discrete equal sampling GSS model to continuous unequal sampling OUSS model is: , , , and (Dennis & Ponciano, 2014). Assuming a stationary distribution for the initial log-abundance population in the time-series (), the OUSS model has four unknown parameters: (mean stationary log-abundance), (the trend parameter, rate to approach to stationarity), (variability of the process noise), and (variability of sampling).

These parameters relate with the GSS model parameters in stationary distribution dynamics as: , , , and ; the normal stationary probability distribution has mean and variance (Dennis & Ponciano, 2014). If the initial log-abundance of the population does not meet this assumption (e.g., it is under transition growth), a nonstationary distribution should be modeled with a different maximum likelihood estimation. The normal transition in nonstationary cases has a mean and variance , adding an extra parameter to estimate (). We modeled the dynamic of the populations for density independence (including initial nonstationary distributions) as EGSS, while stationary distributions as OUSS (see below).

**2.2 | Time-series and local persistence probability from eBird data**

We constructed the time-series eBird data with the maximum count reported per week in sampling units of 100 km2, assuming that this maximum count in eBird is the potential minimum number of individuals in each sampling unit representing populations (Poli et al., 2020). We used Snail Kite (*Rostrhamus sociabilis*) in Florida as our example species. Snail Kite has been extensively monitored in Florida U.S. (Reichert et al., 2020), reflecting spatial movement and lower genetic diversity across wetlands (Poli et al., 2022; Reichert et al., 2020; Robertson et al., 2018). We estimated abundance dynamics from eBird data, accessing records and observer counts through May 2024 from <https://ebird.org/data/download>; based on temporal sampling bias (Backstrom et al., 2024), we concentrate our time-series since 2018 (Supporting Information; Figure SI-1). We constraint the variation of sampling effort in this semi-structured platform following elsewhere recommendations (Backstrom et al., 2024; Johnston et al., 2021; Kelling et al., 2019; Strimas-Mackey et al., 2023). For example, we were only interested in complete checklists from "traveling" or "stationary" protocols within a sampling effort of ≤ 5 hours, ≤ 5 km, ≤ 10 observers, assigning each record to a hexagonal grid of 100 km2 area, assuming population estimation from the maximum observation counts per week in these fixed spatial sampling units (Johnston et al., 2021; Strimas-Mackey et al., 2023). In addition, we limited the records to diurnal events, between 06:00 and 18:00.

Although the high counts per week provide impressive data to estimate parameters, predict latent abundance, and their 95% confidence intervals for time-series at several spatial sampling units (Figure 1), we applied the risk-based population viability monitoring framework to estimate local persistence probability for the locality with more records. This locality correspond to the recently established northern population at the Payne’s Prairie State Park wetland, in Alachua County north-central Florida (Poli et al., 2020). After Hurricane Irma flooded this ~85 km2 wetland system in 2017, Snail kites established a nesting population there in 2018, with a steady increase in abundance (Fink, Auer, et al., 2023) tightly correlating weekly high eBird counts with systematic airboat counts and long-term banding monitoring during this year of establishment (Poli et al., 2020). This range extension reflects changes in wetland conditions that matched with resources availability of novel invasive prey (Machado-Stredel et al., 2024). The resource availability by invasive apple snails have also modified morphological traits (Cattau et al., 2017; Machado-Stredel et al., 2024), driving increase in population growth for the northern Snail kites’ population declines in southern populations (Cattau et al., 2016).

To conduct the population viability monitoring (Staples et al., 2005) for Snail kites in Payne’s Prairie with eBird data, we modeled the trend of the population for the first two years of establishment (2018-2019) using the EGSS model (See SI Section S2 for a graphical step by step, Figures SI-2 to SI-5). With the parameters estimated in this first model, we simulated 10000 trajectories for the following two years (104 weeks) and count the number of trajectories that ended below an assumed critical number of individuals of ¾ the mean of abundance observed in eBird between 2018-2024 (). Then, each new observation by week was included, the model fitted, and new projections of trajectories were simulated, storing the probability of declining below our threshold value (*i.e.*, risk to (quasi)extinction). We fitted in each iteration the OUSS, but if the trend parameter , we selected EGSS because it is an indication of density independence ().

**3 | RESULTS**

The eBird record history of Snail Kite in Florida includes 438 sampling units of 100 km2 (figure). After filtering by good practices of sampling effort (Johnston et al., 2021; Strimas-Mackey et al., 2023), we used the time-series for ## sampling units with more than 100 checklists that might reflect different dynamics. For example, a single cell concentrated most of the observations (>7,000). This cell overlaps with most of the Payne’s Prairie State Park wetland



**Figure 1**. Snail Kite population abundance in Payne’s Prairie, north-central Florida. **(a)** Map of spatial sampling effort, each hexagonal cell corresponds to an area of ~100 km2, and the color identify sites with higher sampling in eBird (log10 scale). A single cell in northcentral Florida (~Payne’s Prairie Preserve State Park) concentrated 7,141 checklists (intense yellow color). **(b)** Records of Snail Kite in Payne’s Prairie, showing some popular visited sites within this sampling unit. **(c)** Time-series abundance observed (blue circles, ) and estimated (red squares and solid line, ), with their bootstrapped 95% confidence intervals (gray lines). Estimations with restricted maximum likelihood under Ornstein-Uhlenbeck State-Space model. This model estimates parameters of mean stationary log-abundance ((confidence intervals )) considering the rate of approaching to stationary distribution under density dependence (), variability of the process noise (), and variability of observation noise ().

A graph of a number of numbers

Description automatically generated with medium confidence

**Table 1**. Restricted maximum likelihood estimates (and 95% confidence intervals) for the parameters in the Ornstein-Uhlenbeck State Space model for two subspecies of Apolinar’s Wren in five spatiotemporal sampling unites within the Colombian Eastern Andes. The páramo subspecies (*C. a. hernandezi*) is represented in the Chisacá Lakes system sampling unit, the other four sampling units represent the nominal subspecies (*C. a. apolinari*).

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
| Population (*n* sampling events) |  |  |  |  |
| Chisacá Lakes system (407) | 1.4332  (1.385, 1.472) | 0.0844  (0.468, 9.654) | 0.0163  (3.08 \* 10-6, 0.491) | 0.3692  (0.168, 0.505) |
| Bogotá wetlands (171) | 0.2966  (0.237, 0.352) | 1.1036  (0.401, 19.054) | 0.4613  (0.120, 7.476) | 1.92 \* 10-4  (1.47 \* 10-9, 0.091) |
| Fuquene Lake system (123) | 0.8497  (0.746, 0.936) | 0.8626  (0.793, 15.632) | 0.6696  (0.582, 6.419) | 0.1677  (2.07 \* 10-5, 0.555) |
| Tota Lake system – north (101) | 1.1863  (1.152, 1.340) | 0.9497  (1.094, 18.633) | 1.0037  (1.225, 23.050) | 6.30 \* 10-6  (4.59 \* 10-9, 0.241) |
| Tota Lake system – south (100) | 0.8892  (0.757, 0.936) | 0.3698  (0.159, 12.749) | 0.2352  (0.060, 2.436) | 0.0897  (1.14 \* 10-6, 0.464) |

**DISCUSSION**

It works. It differs from previous. We have opportunities.

For instance, state-space models could be extended to intrinsic conditional autoregressive models with parameters of variation of estimates for neighboring populations (Besag et al. 1991, Bled et el. 2013).

Test hypotheses: different populations have different dynamic, thus a particular SS case (EGSS, OUSS.NoSt, OUSS.St). Further hypotheses could include movement in Snail Kite?

Different community science data can be integrated with rigorous traditional surveys to estimate abundance in an effective way (Zhao et al., 2024). The problem arises when there are not traditional surveys to integrate community science data. Nonetheless,

Spatiotemporal subsampling in hexagonal grids to eBird data provide a measure of abundance density from community science data. We extracted the maximum value observed per day within a sampling unit, which provide a way to include more data in the time-series construction.

For example, population trends from eBird have used discrete-time stochastic exponential growth rate models (Fink, Johnston, et al., 2023). We used a similar model, EGSS, as our null hypothesis for density dependence. Including the density dependence estimation in the population growth model for stationary and nonstationary trends (OUSS) we improve decisions?

Our practical approach follows the probability distribution suggested in the original formulation of GSS (Dennis et al., 2006). Nonetheless, the model could be easily modified, like changing the observation process from a log-normal distribution to a Poisson distribution with scaling parameters linking detection probabilities or other covariates (Zhao et al., 2024). In addition, include immigration and emigration to open populations monitored by community science data?

The Kunming-Montreal Global Biodiversity Framework Goal A states that “*by 2050, the extinction rate and risk of all species are reduced tenfold and the abundance of native wild species is increased to healthy and resilient levels*”. It might be difficult to monitoring the reduction of risk of all species, or the increase of native wild species. Community science data provide an integrative approach for our society. Here we show that although eBird abundances underestimate the number of individuals, it is possible to track the population dynamics and estimate risk of extinction through time.

**ACKNOLEDGEMENTS**

We are in dept with the many volunteers that report under good practices data to eBird, they are making the differences with the power of people. O.A.C. received departmental funding at the University of Florida, such as the College of Agricultural and Life Science Dean’s Award, the Doris and Earl Lowe and Verna Lowe CALS Scholarship, as well as the SNRE Robin E. Nadeau Graduate Research Award.

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**Supporting Information for**

**Risk-based viable population monitoring from community science data**

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**Section S1: Temporal bias of eBird records for Snail kites in Florida**

**A graph of a number of kites

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**Figure SI-1.** Histogram of the number of eBird checklists per year for Florida Snail kites. Red lines indicate our temporal sampling bias threshold (more than 1000 checklists per year), concentrating our sampling between January 2018 and May 2024.

**Section S2: Step by step of a Population Viability Monitoring (or risk-based viable population monitoring) for Snail kites abundance records in eBird**

1. Fit an EGSS model for the first two years (2018-2019).

A graph of a number of people

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**Figure SI-2**. (*LEFT*) eBird observation (blue circles) and Exponential Growth State-Space model prediction (red triangles) for Snail kites in Payne’s Prairie, Alachua County, north-central Florida, during the first two years (2018-2019; weeks 1 to 104 in the time series). Black dots represent observations following standardized methods for 2018 (Poli et al., 2020). (*RIGTH*) With this first model, we can identify an underestimation of the abundance by a factor of 4.2 during the first year of standardized monitoring.

1. With the model parameters, project trajectories for the following two years (104 weeks) and estimate probability of going below a threshold (e.g., 1/2 mean of the Population abundance of all time-series).

A graph of a graph with numbers and a line

Description automatically generated with medium confidence

**Figure SI-3**. First projection of the population of Snail Kite in Payne’s Prairie wetland for two years after the first two years of establishment (2018-2019). The figure depicts 1000 trajectories that end after two years of simulation below (red lines) or above (gray lines) of 6 individuals (our assumed for pseudo extinction).

1. Add the next week of observation, estimate again the model parameters, and project again two years ahead (104 weeks), estimating probability of going below a threshold. From this point on, we can fit OUSS, but if the trend parameter , we selected EGSS because it is an indication of density independence ().

**A graph of a number of bird species

Description automatically generated with medium confidence**

**Figure SI-4**. New fitted model, including observation. Although the OUSS model was fitted, the trend parameter indicated density independence, suggesting the use of the EGSS model. With the new parameters estimated for the EGSS model, the population trajectories are simulated 2 years ahead (104 weeks), estimating an update probability to end below a threshold (**P(ext risk)**).

1. Iterate the process for the following periods. We can subsample some moments to illustrate the iteration, for instance in weeks 104 (December 2019), 129 (June 2020), 154 (December 2020), 179 (June 2021), 206 (December 2021), 231 (June 2022), 256 (November 2022), 281 (May 2023), and 306 (November 2023). The model selected in each period projection is also stored (see week 206-December 2021).

**A group of graphs showing different types of plants

Description automatically generated with medium confidence**

**Figure SI-5**. Nine weeks across the time-series of Snail kites’ abundance in Payne’s Prairie, illustrating the population viability monitoring methodology. The models (OUSS or EGSS) are fitted in each period, with . Use of the EGSS model depends on assessing if the trend parameter in the OUSS indicated density independence (). With the new parameters estimated in each period, the population trajectories are simulated 2 years ahead (104 weeks), and probability to end below a threshold is estimated (**P(ext risk)**).