BATIS: Bayesian Approaches for Targeted Improvement of Species Distribution Models

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Abstract

Species distribution models (SDMs), which aim to predict species occurrence based on environmental variables, are widely used to monitor and respond to biodiversity change. Recent deep learning advances for SDMs have been shown to perform well on complex and heterogeneous datasets, but their effectiveness remains limited by spatial biases in the data. In this paper, we revisit deep SDMs from a Bayesian perspective and introduce BATIS, a novel and practical framework wherein prior predictions are updated iteratively using limited observational data. Models must appropriately capture both aleatoric and epistemic uncertainty to effectively combine fine-grained local insights with broader ecological patterns. We benchmark an extensive set of uncertainty quantification approaches on a novel dataset including citizen science observations from the eBird platform. Our empirical study shows how Bayesian deep learning approaches can greatly improve the reliability of SDMs in data-scarce locations, which can contribute to ecological understanding and conservation efforts.

Code — https://github.com/cath34/batis
Datasets — https://huggingface.co/datasets/cathv/BATIS
Extended version — https://arxiv.org/abs/2510.19749

1 Introduction

Understanding the factors governing the spatial distribution of species is a long-standing topic of interest in ecology (de Candolle 1855; Thuiller et al. 2015). The rapid loss of biodiversity further highlights the need to better understand species distributions and conservation status, which requires robust modeling methods (Sharma et al. 2025). *Species distribution models* (SDMs) are at the forefront of this research, enabling ecologists to predict and understand species occurrence by linking observational data (presence or absence) to environmental covariates (Elith and Leathwick 2009). These models have proved to be essential tools to support conservation planning and management (Jetz et al. 2019), with notable examples including predicting species range shift (Chauvier-Mendes et al. 2024), mapping invasive species risk (Davis et al. 2024), supporting translocation programs (Draper, Marques, and Iriondo 2019), reducing bycatch rates in fisheries (Hazen et al. 2018), and informing IUCN Red List assessments (Syfert et al. 2014).

SDMs are traditionally based on statistical approaches, offering strong interpretability and theoretical grounding. However these methods often rely on restrictive assumptions such as linearity, leading them to struggle with high-dimensional datasets. Recently, deep learning approaches to SDMs proposed to overcome these challenges and were shown to consistently outperform statistical ecology methods for large and heterogeneous datasets (Deneu et al. 2021).

Although a wide variety of SDM approaches have now been introduced, their effectiveness at large spatio-temporal scales remains hindered by the abundance and geographical coverage of the data used to train them (Van Proosdij et al. 2016). In most cases, observations are disproportionately concentrated in areas easily accessible by roads (Kadmon, Farber, and Danin 2004) and with high human population densities (Speed et al. 2018). In contrast, remote locations are most often associated with very limited to no observations, as illustrated in Fig. 1.

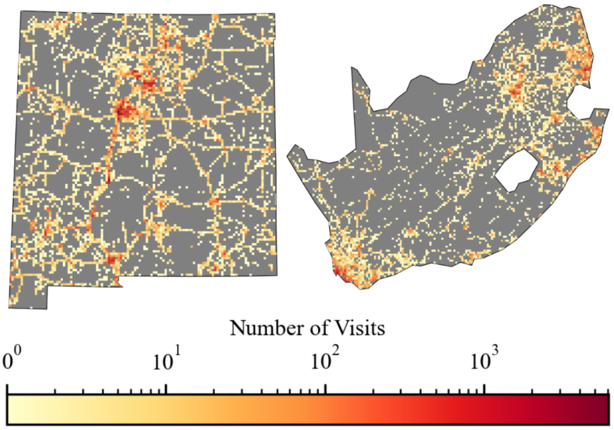

Figure 1: Distribution of citizen science sampling trips across New Mexico, US (left) and South Africa (right), retrieved from the eBird database for the whole year of 2024. The value assigned to each 5km^2 (US) and 10km^2 (South Africa) grid cell corresponds to the total number of visits that were registered within that cell.

Data distribution biases especially affect machine learning-based approaches, which typically rely on trustworthy labeled data. Limited observations in a given location can lead to poor estimates of species occurrence (Fink et al. 2020) – essentially, noisy labels – and naïvely incorporating such data points in model training can degrade performance. However, sparse observations still offer potentially valuable information, and finding ways to properly leverage it could help improve SDMs and guide conservation efforts in remote or underresourced areas. We argue that uncertainty-aware methods can offer a principled way of leveraging limited location-specific observations, enabling controlled prediction updates that can balance global-scale models with local-scale observations.

In this work, we tackle the spatial heterogeneity challenge of biodiversity data by revisiting species distribution modeling from a Bayesian perspective, introducing **BATIS**, a framework enabling the application of **B**ayesian **A**pproaches for **T**argeted **I**mprovement of **S**pecies distribution models (named after the batis, a bird found in sub-Saharan Africa). In this framework, prior predictions from ML are iteratively refined offline with limited field observations in data-scarce locations, testing the ability of ML models to capture both the epistemic (model-inherent) and aleatoric (data-inherent) uncertainty of SDM data. Quantifying epistemic uncertainty provides a measure of the model's confidence in its prior predictions and highlights how informative additional field observations could be, while measuring aleatoric uncertainty ensures that the noise associated with the additional data is appropriately taken into account. We present an empirical study of a variety of uncertainty-aware ML approaches approaches on this task, using a novel large-scale dataset.

- We introduce the framework of iteratively refining the prior predictions of an uncertainty-aware SDM with the help of limited additional on-the-ground information.
- We benchmark a variety of state-of-the-art uncertainty estimation ML methods on the above framework, and present a novel dataset derived from eBird (Sullivan et al. 2009), building on the SatBird (Teng et al. 2023) dataset.
- We find that our framework can rapidly improve predicted species distribution models in data-scarce locations, even with minimal additional ground truth data ($<$10 samples), effectively combining broader ecological patterns with fine-grained, location-specific insights.
- We provide evidence that machine learning approaches relying on aleatoric uncertainty are the most effective at improving predictions in low-data regimes.

BATIS can be seen as an innovative way of coupling the predictive power of modern deep learning to the statistical rigor of traditional hierarchical inference, thereby creating a bridge between ML and established methods in ecology. Our code and datasets are available open-source.

2 Related Works

Machine Learning for SDMs. Species distributions have been widely estimated from environmental data with statistical ecology methods. Popular SDMs in ecology include techniques based on maximum entropy (MaxEnt) (Phillips, Dudík, and Schapire 2004), random forests (Valavi et al. 2021), and generalized linear models (Guisan, Edwards, and Hastie 2002). More recently, a wide variety of deep learning approaches have been introduced, including simple multi-layer perceptrons (Zbinden et al. 2024), computer vision methods leveraging remote sensing imagery (Estopinan et al. 2022; Teng et al. 2023) or location embeddings (Cole et al. 2023), and even language-based reasoning methods (Hamilton et al. 2024). Active learning (Lange et al. 2023) and few-shot learning (Lange et al. 2025) frameworks have also been introduced. Deep learning models have been shown to consistently outperform traditional approaches in ecology (Deneu et al. 2021), notably when applied to large-scale citizen science datasets (Davis et al. 2023).

Some deep learning-based SDMs have focused on estimating binary species range maps (Dorm et al. 2024). This corresponds to a multi-label classification problem in which the list of species that *can* be encountered at a given location is predicted, regardless of the frequency at which they are observed. Another important challenge is *encounter rate estimation*, i.e. a multi-output regression problem aimed at predicting the average rate at which observers encounter species at a given location (Johnston et al. 2021). The use of ML for predicting encounter rates has been explored in Teng et al. (2023) and Abdelwahed, Teng, and Rolnick (2024), a line of work which we follow here. Encounter rates are closely linked to the notion of *occupancy*, i.e. the probability of a species occupying a given site. Occupancy is a core concept in ecology (MacKenzie 2018), and understanding occupancy patterns is essential for prioritizing conservation efforts. Because encounter rates can be seen as the product of occupancy and detection probability (Johnston et al. 2021), they can provide a more nuanced and realistic representation of species distributions than binary range maps.

Bayesian Inference for SDMs. In statistical ecology, SDMs have been estimated in a Bayesian context using computationally intensive algorithms, such as Markov Chain Monte Carlo (MCMC) approaches (Zulian, Miller, and Ferraz 2021) and integrated nested Laplace approximation (Omre, Fjeldstad, and Forberg 2024). Golding and Purse (2016) proposed a more flexible approach based on Gaussian processes, but this was applicable only to a limited number of species and covariates. Our work is the first to reframe deep learning-based SDMs under a Bayesian perspective.

Uncertainty Quantification for SDMs. Uncertainty quantification is recognized by ecologists as a major challenge for SDMs (Yates et al. 2018). To date, however, the vast majority of works do not investigate the effects of uncertainty on model outputs (Zurell et al. 2020). Only a limited number of statistical tools have been proposed to measure and incorporate uncertainty estimates into SDMs (Beale and Lennon 2012), and these tools are not easily scalable, as they often require computationally expensive MCMC iterations to estimate posterior probability distributions (Rocchini et al. 2019). Thus, they are only appropriate for SDMs relying on a very small number of covariates and species. Approximation techniques such as model ensembling (Guo et al. 2015) have been applied to quantify uncertainty in SDMs (Convertino et al. 2012), but their use remain limited. Recently, an active learning framework was proposed to sequentially select geographic locations that would best reduce uncertainty of an SDM for previously unmapped species Lange et al. (2023). This work however does not take a Bayesian approach to improving predictions, instead estimating uncertainty via disagreement across an ensemble of models to guide the active learning step.

Uncertainty Quantification in Deep Learning. An extensive variety of approaches have been proposed to approximate uncertainty in the Bayesian deep learning literature, since computing a posterior distribution over the parameters of a neural network according to the rule of Bayesian inference is analytically intractable (Band et al. 2021). However, these approaches have mostly been tested on generic vision benchmarks (Mucsányi, Kirchhof, and Oh 2024) such as CIFAR-10 (Krizhevsky 2009) and ImageNet-1k (Deng et al. 2009), which do not reflect the complexity of real-world tasks. Our work is the first to integrate such approaches for solving a complex ecological task.

3 The BATIS Framework

Species Encounter Rate Estimation

We here formalize the problem of species distribution modeling in the context of checklist-based surveys (presence-absence data) from ecologists and/or citizen science platforms. Let L be a region of interest, and $\mathcal{S} = \{s_1, \ldots, s_N\}$ be a set of N species that may potentially exist within L. We consider observations within L as occurring at one of a set of K discrete *hotspots* $\mathcal{H} = \{h_1, \ldots, h_K\}$, each representing an area in which observers can record species (e.g. a park, geographic feature, or address). To each hotspot $h_k \in \{1, \ldots, K\}$ is associated a set of checklists $\mathcal{C}_k = \{\mathbf{c}_j\}_{j=1}^{|\mathcal{C}_k|}$, where each checklist $\mathbf{c}_j \in \{0,1\}^N$ indicates which of the N species are recorded as present (1) or absent (0) during an observer's visit to the location. For any (non-empty) set $\mathcal{C}_k$ we define $p_{i,k}$ of species i at hotspot k to be the rate at which i is reported across checklists:

$$p_{i,k} := \frac{1}{|\mathcal{C}_k|} \sum_{\mathbf{c}_j \in \mathcal{C}_k} \mathbf{c}_{i,j} \tag{1}$$

It is a standard assumption that as $|\mathcal{C}_k| \to \infty$ (assuming a diversity of observers, observation dates, etc.), the value $p_{i,k}$ converges to an ecological quantity, the *encounter rate* $p_{i,k}^{\infty}$, representing the chance that a random observer will encounter species i at h_k on any given occasion.

Following Teng et al. (2023); Abdelwahed, Teng, and Rolnick (2024), we consider a machine learning formulation of species distribution modeling in which the encounter rate $p_{i,k}^{\infty}$ is to be estimated for each species i, given a set of information associated with the hotspot h_k – e.g., average precipitation, temperature, etc., as well as satellite imagery of the location. In practice, of course, the ground truth value $p_{i,k}^{\infty}$ is not directly observable, but is well-approximated by $p_{i,k}$ for hotspots h_k where $|\mathcal{C}_k|$ is sufficiently large; therefore the task is to estimate $p_{i,k}$.

Bayesian Estimates of Encounter Rates

For hotspot $h_k \in \mathcal{H}$, let $C_{i,k} = p_{i,k} \cdot |\mathcal{C}_k|$ be the number of times species i was observed at h_k. Then, we may assume that $C_{i,k}$ follows a binomial distribution parameterized by the true encounter rate – i.e. $C_{i,k} \sim \text{Binomial}(J, p_{i,k}^{\infty})$. This simple assumption allows us to formulate a *Bayesian inference problem*, in which we place a *Beta prior* over $p_{i,k}^{\infty}$:

$$p_{i,k}^{\infty} \sim \text{Beta}(\alpha_{i,k}, \beta_{i,k}) \tag{2}$$

Instead of estimating $p_{i,k}^{\infty}$ directly, we may consider instead the problem of estimating the parameters $\alpha_{i,k}$ and $\beta_{i,k}$, which can be defined by the closed-form equations

$$\alpha_{i,k} = \mu_{i,k} \left(\frac{\mu_{i,k}(1 - \mu_{i,k})}{\sigma_{i,k}^2} - 1 \right) \tag{3}$$

$$\beta_{i,k} = (1 - \mu_{i,k}) \left(\frac{\mu_{i,k}(1 - \mu_{i,k})}{\sigma_{i,k}^2} - 1 \right) \tag{4}$$

where at each point $\mu_{i,k} \in [0,1]$ encodes our best estimate of the encounter rate of species i at h_k, and $\sigma_{i,k}^2 \leq \mu_{i,k}(1 - \mu_{i,k})$ encodes our uncertainty about that belief.

While previous approaches of predicting species distributions using environmental variables made it possible to estimate encounter rates at a location without incorporating observations at the location, our Bayesian framework makes it possible to combine broad patterns learned by the SDM with any individual checklists recorded at the location in question. Namely, we may consider the output of an SDM to be an initial estimate of $\alpha_{i,k}$ and $\beta_{i,k}$, and we may then incorporate additional information from a checklist of observations by performing a Bayesian update to these parameters to obtain the posterior. In the Beta distribution, this update takes a convenient form: $\alpha_{i,k} := \alpha_{i,k} + \sum_{\mathbf{c}'_j \in \mathcal{C}'_k} \mathbf{c}'_{i,j}$ and $\beta_{i,k} := \beta_{i,k} + 1 - \sum_{\mathbf{c}'_j \in \mathcal{C}'_k} \mathbf{c}'_{i,j}$.

Our Bayesian reformulation of the species distribution modeling problem thus allows us to iteratively update prior encounter rates predictions coming from an ML model with additional field observations as they are recorded.

Applications

Our approach can significantly improve encounter rate predictions in data-scarce regions (see section 5). Specifically, our framework is useful since, due to the geographic distribution of species observational data, most locations have a small but meaningful number of observations – that is, there are insufficient observations to reliably calculate the encounter rate empirically, yet enough observations that they contain valuable information. BATIS is particularly well-suited for location-specific ecological questions, such as assessing changes in habitat use and monitoring threatened species presence in protected areas. Moreover, because it allows for fast and lightweight updates of prior predictions, our framework is ideal for integrating daily or weekly updates from citizen science databases such as eBird or iNaturalist (iNaturalist), which are continuously growing, into the SDMs used to inform conservation and land use decisions.

4 The BATIS Benchmark

Dataset

We introduce a dataset for the BATIS framework. We rely on the eBird citizen science database (Sullivan et al. 2009), containing millions of bird observations across the globe standardized in the form of *checklists*, indicating which species were seen or not during a given survey trip. This large amount of data allows us to create a benchmark of test cases that mirrors the real-world scenarios in which BATIS can be applied. We can notably simulate data-deficient locations by providing partial information to SDM algorithms so as to test their generalization capabilities against full ground-truth data. Although eBird strictly focuses on birds, its structure and scale makes it an ideal setting for evaluating BATIS methods, which we hope may then be applied to less standardized datasets, such as those available through GBIF.

Following Teng et al. (2023), we first extracted complete checklists from all hotspots associated with the mainland portions of Kenya (KE), South Africa (ZA), and the contiguous United States. For the US, we followed the same approach as Teng et al. (2023), splitting the dataset into two seasons: summer (US-S, breeding period) and winter (US-W, non-breeding period). We did not consider seasonality for the KE and ZA datasets, as these regions have significantly fewer available checklists and seasonal migrations are also less pronounced in KE and ZA than in the US. Table 1 summarizes the composition of each subdataset. Further details on the dataset can be found in Appendix A.

	KE	ZA	US-W	US-S
Start Date	01/01/10	01/01/18	01/12/22	01/06/22
End Date	31/12/23	17/06/24	31/01/23	31/07/22
N. Species	1,054	755	670	670
N. Hotspots	8,551	6,643	45,882	98,443
N. Checklists	44,852	498,867	3,673,742	3,920,846

Table 1: Summary of the composition of the four subdatasets

Remote Sensing Variables. Our dataset also includes bioclimatic rasters from the WorldClim2.1 model (1km resolution) and Sentinel-2 satellite images (10m resolution) for each hotspot. These serve as predictive variables (inputs) to the models we test, and were selected based on the work of Teng et al. (2023). More information on these variables can be found in Appendix A.

Splits. We reserved 50% of the hotspots with ≥ 15 checklists for the test set (15 being a large enough value to reliably estimate the true encounter rate $p_{i,k}^{\infty}$). The remaining hotspots were split into training and validation sets in a 80:20 ratio, and we used DBSCAN to cluster hotspots and proportionally distribute them across splits, which prevents auto-correlation and over-fitting (Roberts et al. 2017). Table 5 (Appendix A) summarizes the content of each split.

Uncertainty-Agnostic Methods

We considered four SDM baselines in our benchmark. The first one, referred to as **Mean Encounter Rate**, simply predicts the average encounter rate on the training set for each species, ignoring the inputs. We also include a **Random Forest** baseline trained from bioclimatic variables only, as this is a frequently used approach in ecology. Because bioclimatic variables are still almost always exclusively used in ecology, we include a **Multi-Layer Perceptron Model (MLP)** solely trained from these inputs. Finally, we consider the **ResNet-18** approach introduced by Teng et al. (2023), as it was shown to be the best performing model among the SatBird benchmark. The ResNet-18 relies on both bioclimatic variables and satellite imagery as inputs. More information on each of our SDM baselines can be found in Appendix F.

Uncertainty-Aware Methods

We considered the uncertainty estimation approaches listed below. Except for the Fixed and Historical Variance baselines, we restricted ourselves exclusively to distributional approaches, as they offer a more principled way of estimating both the mean and variance of each predicted encounter rate (Mucsányi, Kirchhof, and Oh 2024). More details on each approach can be found in Appendix F.

Fixed Variance. Let $\widehat{\mu}$ be the encounter rate predicted by an SDM. Our Fixed Variance (FV) baseline directly considers $\widehat{\mu}$ as the mean, and fixes a pre-determined variance $\widehat{\sigma^2}$ to initialize the prior. The pre-determined variance must be contained within $\widehat{\sigma^2} \leq \widehat{\mu}(1-\widehat{\mu})$ to maintain a valid Beta distribution. FV also includes a hyperparameter $\tau \in (0, 1]$ to finetune $\widehat{\sigma^2}$ more easily:

$$\widehat{\sigma^2} = \tau \cdot \widehat{\mu}(1-\widehat{\mu}). \tag{5}$$

We considered $\tau = 1$ in our experiments, as we were interested in investigating the behavior of FV when the non-informative $\mathrm{Beta}(0, 0)$ distribution is assigned as the prior.

Historical Variance. Our Historical Variance (HV) baseline computes $\widehat{\sigma^2}$ from past checklists instead, which can be viewed as a way of trying to integrate the uncertainty associated with the data collection process into our framework. In edge cases where $\widehat{\sigma^2} > \widehat{\mu}(1-\widehat{\mu})$, the variance is instead fixed at $\widehat{\sigma^2} = \widehat{\mu}(1-\widehat{\mu})$. In our experiments, we limited the number of past checklists used to compute the prior variance to 5, as we are interested in how this method performs in a low-data regime.

Monte-Carlo Dropout (Gal and Ghahramani 2016). MC Dropout (MCD) can be shown to be a variational approximation of a deep Gaussian process (Gal and Ghahramani 2016). A proportion of neurons are randomly deactivated at training and test time, and M forward passes are used to compute mean and variance for each location. MCD is primarily effective at capturing epistemic uncertainty.

Deep Ensembles (Lakshminarayanan, Pritzel, and Blundell 2017). In Deep Ensembles (DE), an ensemble of M

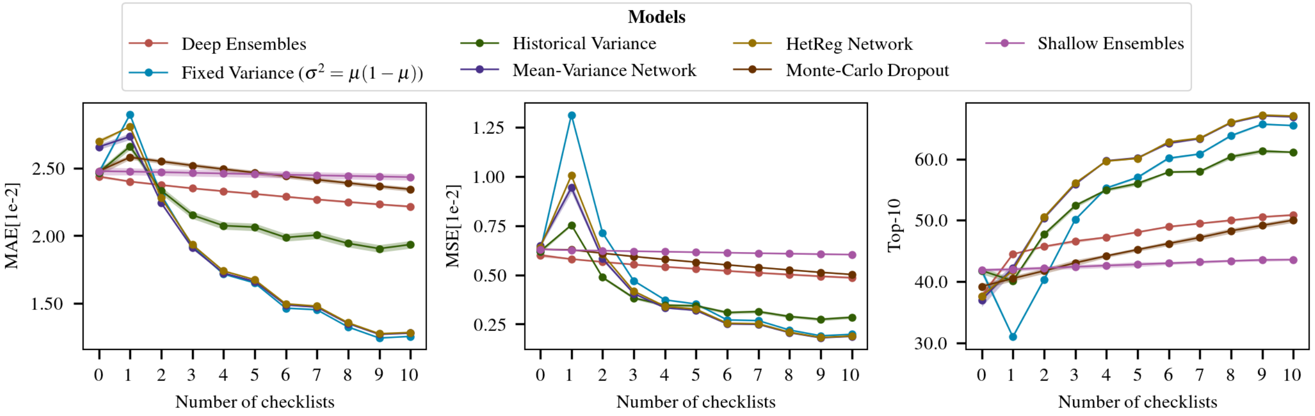

Figure 2: Iterative improvements for the different uncertainty estimation approaches with increasing number of checklist updates for the MAE, MSE and Top-10 metrics on the South Africa Region test set. We report the mean on three seeds and standard deviations for each model. 505.89pt

neural networks are independently trained on the same task, and their individual predictions on the same input can be used to estimate mean and variance. Despite its simplicity, DE is the current state-of-the-art for estimating epistemic uncertainty in deep learning (Mukhoti et al. 2021).

Shallow-Ensembles (Lee et al. 2015). Shallow Ensembles (SE) aim to offer a computationally cheaper alternative to DE by using a shared backbone and M output heads. The mean and variance of each predictions can be estimated by averaging the outputs of the M heads.

Mean-Variance Network (Nix and Weigend 1994; Sluijterman, Cator, and Heskes 2023) . A Mean-Variance Network (MVN) maps each location to two outputs: a predicted mean encounter rate vector and a predicted variance vector. The predicted variance can be considered as a measure of aleatoric uncertainty, as it aims to reflect the inherent task difficulty. MVNs are trained using the Gaussian negative log-likelihood loss function, presuming that encounter rates are normally distributed, which results in an increase in predicted variance when the predicted mean encounter rate differs greatly from the ground truth value.

Heteroscedastic Regression Neural Network (Kendall and Gal 2017). A Heteroscedastic Regression Neural Network (HetReg) is very similar to an MVN, but adds MC Dropout sampling to simultaneously quantify aleatoric and epistemic uncertainty. M dropout passes are used to compute the mean encounter rate vector, and variance is estimated by adding epistemic uncertainty (variance computed from M predicted encounter rates) to aleatoric uncertainty (mean computed from M predicted variances).

Experiments

We performed the experiments described below. Training protocol details, including hyperparameters, and compute resources can be found in Appendix G.

Overall performance. We trained each model on each of the four subdatasets. We report baseline performance for each model in Table 2. Then, we investigate how the framework introduced in section 3 with the uncertainty quantification approaches described in section 4 can improve these baseline results. We report performance after updating the posterior distribution of each hotspot with five new checklists for each model.

Region-specific episodic behavior. We investigate the episodic behavior of our proposed Bayesian framework for the MLP and ResNet-18 models. We study how average performance evolves as we iteratively update the posterior distributions associated with each hotspot of our test set, for up to ten checklists.

Species-specific episodic behavior. We study how our proposed framework can be potentially leveraged to improve the reliability of range maps for individual species in low-data regimes. To do so, we consider how the absolute error between the predicted and ground truth encounter rates for a single species changes as we iteratively update the posterior distribution across an entire region.

Metrics. We evaluate our methods with the same metrics as Teng et al. (2023), namely MAE, MSE, Top-10, Top-30, and Top-k accuracy. Further details on these metrics are provided in Appendix G.

5 Results and Discussion

Overall results. Table 2 details the performance of uncertain-agnostic and uncertainty-aware models on the KE and ZA subdatasets. Results for the US can be found in Tables 10 and 11 in Appendix H. We observe that uncertainty-aware methods significantly outperforms all the uncertainty-agnostic approaches on our test set, even when prior predictions are updated with five checklists only. This suggests that our Bayesian approach to SDM estimation could greatly improve the reliability of predictions in data-scarce locations.

Our proposed framework essentially merges the strengths of traditional tools for Earth-scale mapping, which can make estimates for large regions with high throughput, and of ground-based surveys, which can record specific and accurate data with high effort.

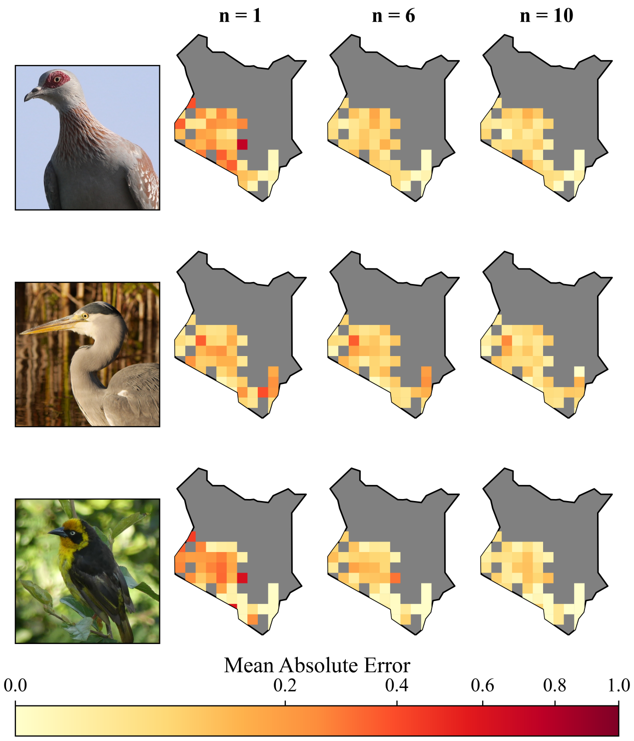

Figure 3: Evolution of the MAE in relation to the number of checklists (1, 6, 10) used to update the posterior distribution for three bird species of Kenya (*Columba guinea*, *Ardea cinerea*, *Ploceus baglafecht*) . The value assigned to each 70km^2 grid cell corresponds to the mean MAE computed on the aggregation of all the hotspots located within that cell.

Iterative Improvements by Region. Figure 2 shows the evolution of the performance of the uncertainty-aware approaches with increasing number of checklist updates, on the ZA subdataset. Similar figures for the KE and US subdatasets are provided in Appendix H. We observe that our Bayesian framework requires as few as one or two checklists to significantly outperform static baselines. MVN and HetReg are the top-performing methods in our benchmark, with HetReg performing only marginally better than MVN. This is likely because HetReg and MVN share a common aleatoric uncertainty quantification module, but HetReg also includes an epistemic uncertainty estimation module. Estimating epistemic uncertainty alone, however, does not significantly improve on static baselines, as demonstrated by the limited improvements in performance with Deep Ensembles. Our findings are consistent across all four subdatasets. Interestingly, we also observe that the Fixed Variance baseline reaches MAE and MSE performance comparable to HetReg/MVN after 10 checklists, when the prior variance is fixed to its maximum theoretical value.

Iterative Improvements by Species. As shown in Fig. 3, our approach rapidly improves encounter rate predictions for species in data-scarce locations. The error quickly drops as more checklists update the posterior distributions, and the improvements are consistent across all hotspots. Our approach shows potential for generating more reliable range maps in areas where a given species has been observed only a handful of times. This could be especially valuable for conservationists monitoring rare or endangered species in areas where gathering additional observations is challenging.

Aleatoric vs. epistemic uncertainty. We find that models relying on aleatoric uncertainty (such as HetReg and MVN) perform better than those which rely on epistemic uncertainty (such as DE and MCD). This likely results from two factors: First, with real-world observation-based data, similar conditions can occur with very different observations (in this case, reflecting variability in the whereabouts of individual animals and their visibility to an observer). Second, subtle environmental differences may not be fully captured by the input variables. Our conclusions are consistent with trends noted in the Bayesian ML literature (Kendall and Gal 2017), in which it is observed that epistemic uncertainty can be poorly estimated in deep learning models due to the implicit assumption that similar inputs lead to similar outcomes. By contrast, aleatoric uncertainty estimation approaches allow us to capture the inherent unpredictability of species observations and the potential existence of local environmental factors not captured by the prior SDM.

6 Limitations

Effectively combining large-scale ecological patterns with local information remains challenging. There remains tension between the broad environmental variables learned by deep SDMs (our Bayesian prior) and the hotspot-specific features captured by observational information (our updates to that prior). As shown in Figure 2, the initial predictions of an uncertainty-aware SDM can be overwritten in a first Bayesian update, when the estimated prior variance is large. This can lead to an initial drop in performance before enough updates are performed to boost performance, even though performance would ideally increase *monotonically* with number of updates. A simple approach to mitigate such behavior is to consider a weighted average of predictions from the prior and the updated SDM, progressively giving more importance to the updates with more observations. We provide additional experiments showing how such an approach can help smooth the results curve observed in Fig. 2 in Appendix E..

Uncertainty estimation approaches cannot fully correct for biases in citizen science data. Citizen science data is heavily influenced by *predictable* factors such as the day of the week, the time of day, the expertise of the observer, the weather, and the proximity to population centers (Sierra et al. 2025). Such biases are *structured*, which technically violates the randomness assumption of aleatoric uncertainty. Epistemic uncertainty estimation approaches can potentially

	MAE[1e-2]		MSE[1e-2]		Top-10		Top-30		Top-k	
Kenya										
MER	3.94		0.82		1.79		2.63		16.21	
MLP	3.51±0.01		0.81±0.00		0.92±0.07		2.18±0.13		16.92±0.04	
Random Forest	3.57±0.00		1.00±0.00		0.31±0.01		2.05±0.02		17.23±0.01	
ResNet-18	1.87±0.04		0.35±0.01		41.24±1.82		52.93±1.54		68.04±0.75	
ResNet-18+FV	1.87 ±0.04	1.50 ±0.00	0.35 ±0.01	0.26 ±0.00	41.24 ±1.82	51.71 ±0.26	52.93 ±1.54	64.46 ±0.31	68.82 ±0.75	75.26 ±0.63
ResNet-18+HV	1.87 ±0.04	1.67 ±0.03	0.35 ±0.01	0.24 ±0.01	41.24 ±1.82	54.68 ±0.43	52.93 ±1.54	63.03 ±0.63	68.82 ±0.75	65.82 ±0.70
ResNet-18+MVN	2.04 ±0.11	1.52 ±0.03	0.37 ±0.01	0.24 ±0.00	36.33 ±1.07	57.98 ±0.10	48.90 ±1.23	67.97 ±0.17	66.38 ±0.82	61.46 ±2.45
ResNet-18+HetReg	2.04 ±0.02	1.52 ±0.01	0.37 ±0.01	0.25 ±0.00	36.24 ±1.06	57.98 ±0.13	49.11 ±0.53	67.82 ±0.09	66.67 ±0.12	61.19 ±0.60
ResNet-18+DE	1.81 ±0.04	1.75 ±0.06	0.32 ±0.01	0.29 ±0.01	44.34 ±0.31	48.47 ±1.06	56.06 ±0.63	59.54 ±1.48	69.94 ±0.53	70.41 ±0.56
ResNet-18+MCD	1.91 ±0.01	1.82 ±0.01	0.37 ±0.01	0.33 ±0.01	38.65 ±1.19	43.15 ±1.01	50.18 ±0.63	54.36 ±0.81	67.18 ±0.11	68.30 ±0.19
ResNet-18+SE	1.73 ±0.01	1.71 ±0.01	0.33 ±0.00	0.32 ±0.00	43.53 ±0.26	44.19 ±0.08	55.79 ±0.41	56.49 ±0.44	70.47 ±0.16	70.70 ±0.16
South Africa										
MER	3.62		0.84		25.53		36.87		49.31	
MLP	2.87±0.00		0.71±0.00		35.17±0.15		51.18±0.4		61.72±0.10	
Random Forest	2.54±0.01		0.69±0.00		38.21±0.16		54.23±0.20		64.26±0.09	
ResNet-18	2.47±0.02		0.62±0.01		41.79±0.59		57.20±0.32		67.11±0.23	
ResNet-18+FV	2.47 ±0.02	1.65 ±0.00	0.62 ±0.01	0.35 ±0.00	41.79 ±0.59	57.00 ±0.17	57.20 ±0.32	69.59 ±0.12	67.11 ±0.23	79.90 ±0.13
ResNet-18+HV	2.47 ±0.04	2.06 ±0.02	0.62 ±0.00	0.34 ±0.00	41.79 ±0.59	56.00 ±0.32	57.20 ±0.32	67.55 ±0.23	67.11 ±0.23	70.79 ±0.13
ResNet-18+MVN	2.66 ±0.02	1.66 ±0.00	0.65 ±0.01	0.32 ±0.00	37.01 ±1.12	60.19 ±0.16	53.20 ±1.06	70.68 ±0.17	64.61 ±0.27	71.88 ±0.35
ResNet-18+HetReg	2.70 ±0.02	1.67 ±0.00	0.64 ±0.00	0.32 ±0.00	37.63 ±0.58	60.10 ±0.03	53.65 ±0.18	70.5 ±0.04	64.84 ±0.17	71.0 ±0.30
ResNet-18+DE	2.44 ±0.01	2.31 ±0.01	0.60 ±0.00	0.53 ±0.00	43.30 ±0.13	48.06 ±0.12	58.47 ±0.06	62.11 ±0.22	67.84 ±0.13	69.72 ±0.09
ResNet-18+MCD	2.61 ±0.01	2.47 ±0.01	0.64 ±0.00	0.56 ±0.00	39.21 ±0.44	45.21 ±0.30	55.00 ±0.40	59.22 ±0.35	65.64 ±0.16	67.86 ±0.20
ResNet-18+SE	2.48 ±0.03	2.46 ±0.02	0.63 ±0.00	0.61 ±0.00	41.90 ±0.22	42.80 ±0.39	56.93 ±0.10	57.67 ±0.13	67.09 ±0.09	67.48 ±0.06

Table 2: Performance of SDM-estimation approaches both without Bayesian updates (left side in split columns) and after updates from five checklists (right side). Note that the first four methods for each region are not uncertainty-aware and therefore cannot be updated with checklist information. Means are shown ± standard deviation across runs. (Note that many standard deviations are quite low; those reported as 0.00 are accurate.)

correct for biases if they can be explicitly modeled, but are unable to do so if they are not encoded in the data. While our work shows that is possible to compensate partially for data gaps associated with the irregular distribution of citizen science data, some biases may affect the accuracy of the underlying numbers used as ground truth, which cannot be compensated for by such methods and remain an active object of inquiry in statistical ecology (Rocchini et al. 2023).

7 Conclusion

In this work, we presented BATIS, a novel framework for species distribution modeling in which uncertainty-aware machine learning approaches are iteratively refined with additional on-the-ground information. Our results show how our framework can rapidly improve SDM predictions in data-scarce locations by combining broader ecological patterns with fine-grained, location-specific insights. Our study also suggests that ML approaches focusing on aleatoric uncertainty provide a better measure of observational variability than those focusing on epistemic uncertainty.

Pathway to impact. SDMs are widely used to inform decisions in conservation, land use, and other areas of impact (Jetz et al. 2019). We hope that BATIS can improve the accuracy of such SDMs in applications where new observations are continually arriving, such as the monitoring of protected areas and endangered species, as well as guiding policies in underresourced or remote regions with lower data availability. Our framework is designed to be readily integrated into existing workflows for creation and utilization of SDMs. In addition, traditional barriers to integration of deep learning into ecology have included computational cost and lack of perceived interpretability. Our proposed approach is computationally lightweight and allow for improved performance without costly retraining, while the focus on uncertainty quantification makes model predictions more transparent, as well as bringing the output closer to the statistical tools already familiar to those working with SDMs.

Future work. Future work includes extending BATIS to guide sampling effort in citizen science initiatives, in collaboration with ecologists, and investigating the behavior of different uncertainty estimation approaches with presence-only data (which are often more abundant and readily available than presence-absence checklist data ; Zbinden et al. (2024)). Finally, an impactful extension of our work would be to control for additional sources of biases in the data, e.g. building on Sierra et al. (2025) by considering subdatasets labeled according to different types of bias.

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