

Stationary Point Acoustic Surveys of Bats on Conservation Lands

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Abstract

The North American Bat Monitoring Program (NABat) has provided a framework for regional biologists to conduct large scale bat acoustic monitoring. Acoustic surveys of this scale often produce large datasets that can assist with conservation and management decisions, but the calls must first be processed and classified to species. Automated classification software is commonly used, but can produce misclassifications. Thus, our objective was to examine different methods of verifying automated classification results to provide useful species presence data. In summer 2018, we conducted stationary point acoustic bat surveys on conservation lands at 158 points within 57 NABat grid cells across Maryland. We used SonoBat 4.2.2 to classify calls to species. To determine species presence, we used three approaches: 1) accepted species classifications, 2) the probability of presence of each species from maximum-likelihood estimates (MLEs), and 3) manually vetted classifications. We then examined differences in the number of cells in which each species was determined to be present by each approach. We collected 178,117 recordings of potential bat calls, 93,983 of which were accepted species classifications in SonoBat. However, even with the lowest MLE confidence level (50%), four WNS-susceptible species and one other species were determined to be present in fewer than 25% of the cells in which their calls were identified. Ten species were present in a greater number of cells based on manual vetting than MLEs. We believe it is necessary to verify automated species classifications. Due to different levels of effort and variation in species presence among the three approaches we tested, it may be best to use a combination such as MLEs with 95% confidence and manual vetting, or false-positive occupancy models, to inform conservation and management decisions.

Introduction

White-nose syndrome (WNS) has been devastating to populations of some hibernating bat species since the introduction of the disease in 2006, and its detection in Maryland in March of 2010 (United States Fish and Wildlife Service 2014). The disease has been found to affect five of the ten bat species that are known to occur in the state. Additionally, wind energy, habitat loss, and climate change may be impacting the state's bats (Kunz et al. 2007; Cryan et al. 2014). To determine the status of bat populations and develop effective management and conservation plans, the Maryland Department of Natural Resources (MD DNR) decided to adopt North American Bat Monitoring Program (Loeb et al. 2015; NABat) stationary point acoustic surveys in 2018.

In a single summer active period, statewide acoustic surveys can be conducted across an entire state, for instance, to provide large scale data on bat presence. However, a single stationary point can produce thousands of potential bat call recordings which must be analyzed. Automated classification software can be used, but may produce misclassifications (Lemen et al. 2015; Russo, Ancillotto, and Jones 2018). Other techniques, such as calculating maximum-likelihood estimates (MLEs) and manual vetting, may be sufficient to determine species presence. Thus, our

objectives were to establish NABat stationary point acoustic surveys in Maryland and to compare species presence based on automated classification results, MLEs, and manual vetting.

Methods

To fill in gaps in knowledge of bat species assemblage, distributions, and habitat use throughout Maryland, we established NABat stationary point acoustic surveys across the state in spring and summer 2018. NABat provides a grid-based framework for spatially balanced, random survey area selection and recommends selecting at least 30 survey areas (cells from the grid) within a state (Loeb et al. 2015). We followed this framework and selected 55 cells within Maryland which contained lands currently managed for conservation (i.e., National Seashore, National Wildlife Refuges, State Wildlife Management Areas, State Parks, The Nature Conservancy lands, etc.), and omitted those which did not.

We worked with regional Department of Natural Resources biologists Dan Feller, Dana Limpert, and Gwenda Brewer to pre-select four survey points within each of the selected cells. The locations of the points were selected to maximize the likelihood of detecting all bat species within the area. In some cells, there was very little conservation land, so not all cells were surveyed with four points, and some points were clustered within cells.

We began surveys in the southeastern part of the state on May 14, 2018, because bats exhibit seasonal activity patterns and this region of the state is typically warmer slightly earlier in the year than other regions. We conducted surveys using 12 Wildlife Acoustics SM4BAT-FS and four SM3BAT acoustic bat detectors with SMM-U2 ultrasonic microphones (Figure 1). For each survey station, we oriented the microphone vertically at the top of a 20-foot (6.1-m) tall mast that was secured with three guy lines. We deployed an iButton temperature logger at each station, which recorded the ambient temperature every 15 minutes for the duration of the survey. Each point was surveyed for four nights, from 15 minutes prior to sunset to 15 minutes after sunrise, unless there was a problem accessing the site or an equipment malfunction. In order to complete the surveys during the active period and before young became volant, we utilized assistance of seven biologists and eight citizen scientist volunteers. In total, their contributions to the project surpassed 200 hours.

To classify calls to species, we used SonoBat 4.2.2 with the Northeastern U.S. classifier, 5 kHz auto-low filter, and 0.80 acceptable call quality. Due to the amount of data we collected, we could not classify all calls in one pass in SonoBat, so we wrote a script to automatically move through the whole dataset, one point at a time, without a human present. We used three approaches to determine species presence within each cell: 1) SonoBat accepted species classifications, 2) SonoBat-calculated cell-level MLEs with four confidence levels (50%, 90%, 95%, and 99%), and 3) manually vetted classifications. To vet classifications, we followed the document provided by NABat, and attempted to classify a single call of each species at each point on each survey night (Reichert et al. 2018). To compare differences in species presence among the three approaches, we produced maps of presence for each species and summarized the number of cells in which each species was present.



Figure 1. An example of an acoustic survey deployment at Assateague Island National Seashore, Maryland.

Results

From May 14, 2018 to July 13, 2018, we completed acoustic surveys at 158 unique points across Maryland, which totaled 576 survey nights (Figure 2). Due to difficulties accessing pre-selected survey points, five of the points were located in cells adjacent to the originally selected cells. Thus, surveys were conducted in a total of 57 cells. These surveys resulted in 178,117 recordings of potential bat calls, and amounted to 577 gigabytes of data. The bat detectors are designed to automatically filter out some noise, but an inspection of a random subset of files revealed that some of the recordings did not contain bat calls.

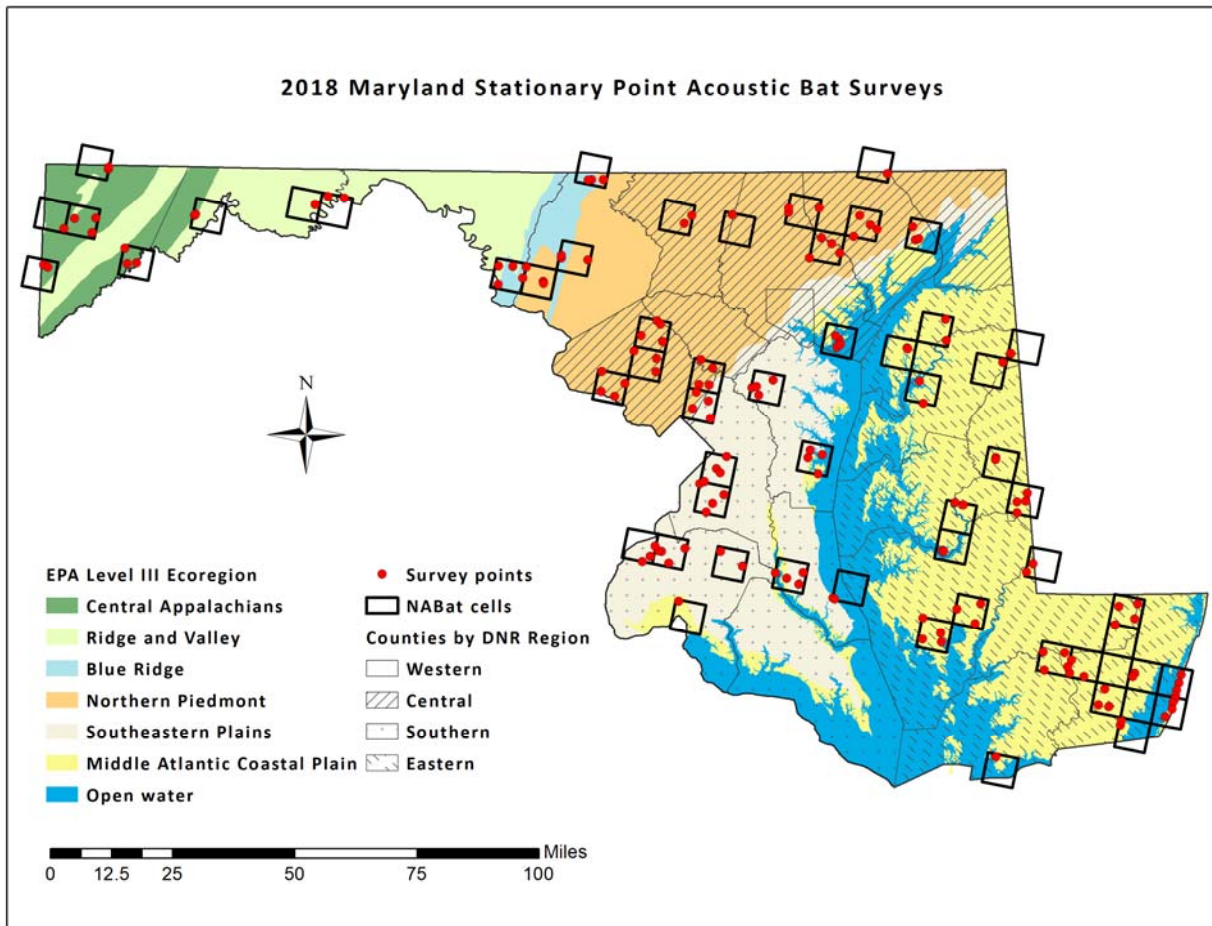


Figure 2. Map of cells and points surveyed throughout Maryland in 2018.

Using SonoBat's automated classification feature, along with our processing script, the initial classification phase took approximately 84 hours (i.e., 3.5 days with the computer running 24 hours per day). This resulted in 93,983 files with accepted species classifications. With this method, every species in the classifier was detected in at least one cell (Table 1).

SonoBat typically calculated MLEs for a single NABat cell (i.e., all points within the cell) in less than two minutes, and this data was gathered by one person in a single day. With MLEs, all species were present in fewer cells than the accepted species method, and no species was present in every cell (Table 1). Based on the 50% confidence level, the four *Myotis* species (all affected by WNS) and NYHU were present in fewer than 25% of the cells in which their calls were accepted classifications by SonoBat. Although some species were present in fewer cells with increasing MLE confidence, we did not see great differences among the four MLE confidence levels.

With NABat's manual vetting approach, it took a single person approximately 520 hours (i.e., three months working a 40 hour work week) to process data from 158 points, most of which had four survey nights. In some cases, this manual vetting approach produced very different results from both MLEs and accepted species classifications. For instance, MYLE, MYSE, NYHU, and

PESU were present in a greater number of cells with vetting than with SonoBat accepted species classifications, and every species was present in a greater number of cells than with MLEs (Figures 2-15). MYLE, MYLU, MYSE, MYSO, NYHU, and PESU were present in cells in which their calls were not classified by SonoBat (Figures 8-11, 14, and 15). Also, MYLU was not present in one cell in which it was present based on MLEs with 99% confidence.

We found that calls of MYLU and MYSO were often very difficult to differentiate, so we produced a map displaying manual vetting presence of the two combined (MYLUSO; Figure 12). There were many calls which we were certain were *Myotis* search phase calls, but we could not classify beyond genus. Thus, we also produced a map displaying manual vetting presence of all *Myotis* (classified to genus or genus and species) combined (Figure 13).

Table 1. Number of cells in which each species was determined to be present based on SonoBat accepted species; MLEs with 50%, 90%, 95%, and 99% confidence; and manual vetting. We surveyed 57 cells in total. Species are Rafinesque's big-eared bat (*Corynorhinus rafinesquii*; CORA), big brown bat (*Eptesicus fuscus*; EPFU), eastern red bat (*Lasiurus borealis*; LABO), hoary bat (*L. cinereus*; LACI), silver-haired bat (*Lasionycteris noctivigans*; LANO), eastern small-footed bat (*Myotis leibii*; MYLE), little brown bat (*M. lucifugus*; MYLU), northern long-eared bat (*M. septentrionalis*; MYSE), Indiana bat (*M. sodalis*; MYSO), evening bat (*Nycticeius humeralis*; NYHU), and tri-colored bat (*Perimyotis subflavus*; PESU). * indicates WNS-affected species.

Species	SonoBat	50%	90%	95%	99%	Vetted
CORA	1	0	0	0	0	0
EPFU	56	55	55	55	55	56
LABO	57	55	54	53	53	57
LACI	56	35	22	20	18	54
LANO	57	39	32	31	28	57
MYLE*	9	1	1	1	1	10
MYLU*	33	2	1	1	1	17
MYSE*	4	1	1	1	1	5
MYSO*	41	3	1	1	1	22
NYHU	47	2	2	1	1	57
PESU*	43	19	16	14	13	51

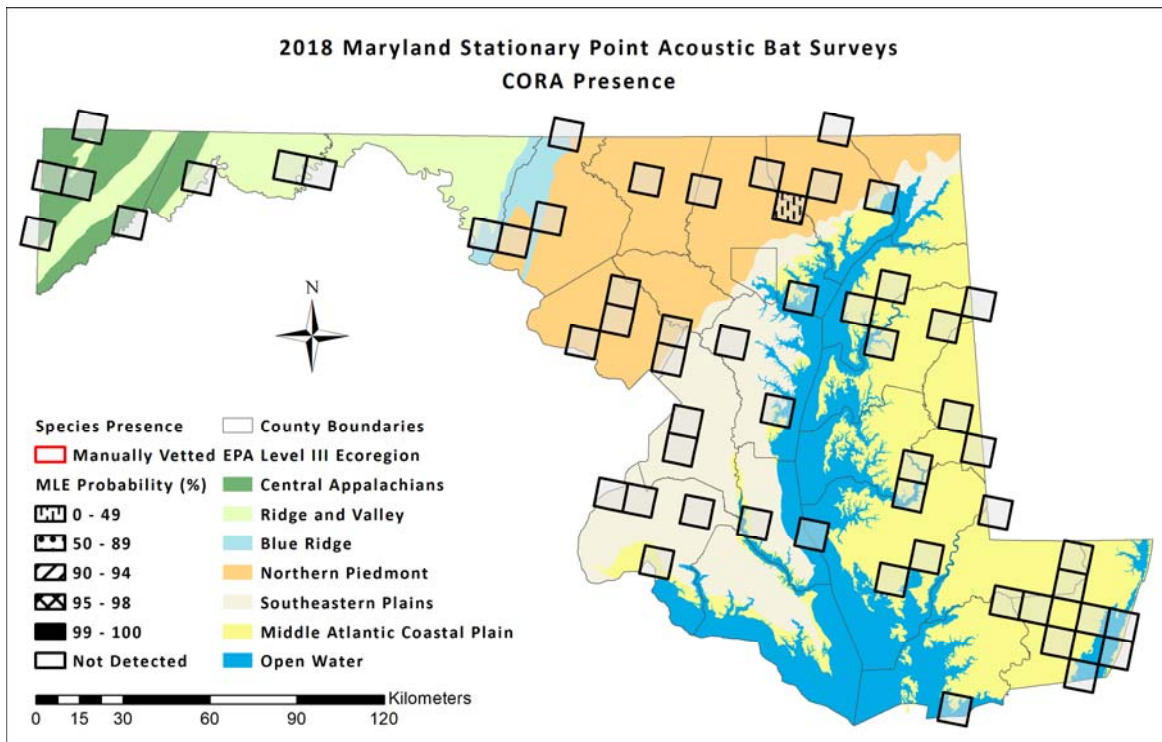


Figure 3. Presence of Rafinesque's big-eared bat (*Corynorhinus rafinesquii*; CORA) based on MLEs and manual vetting.

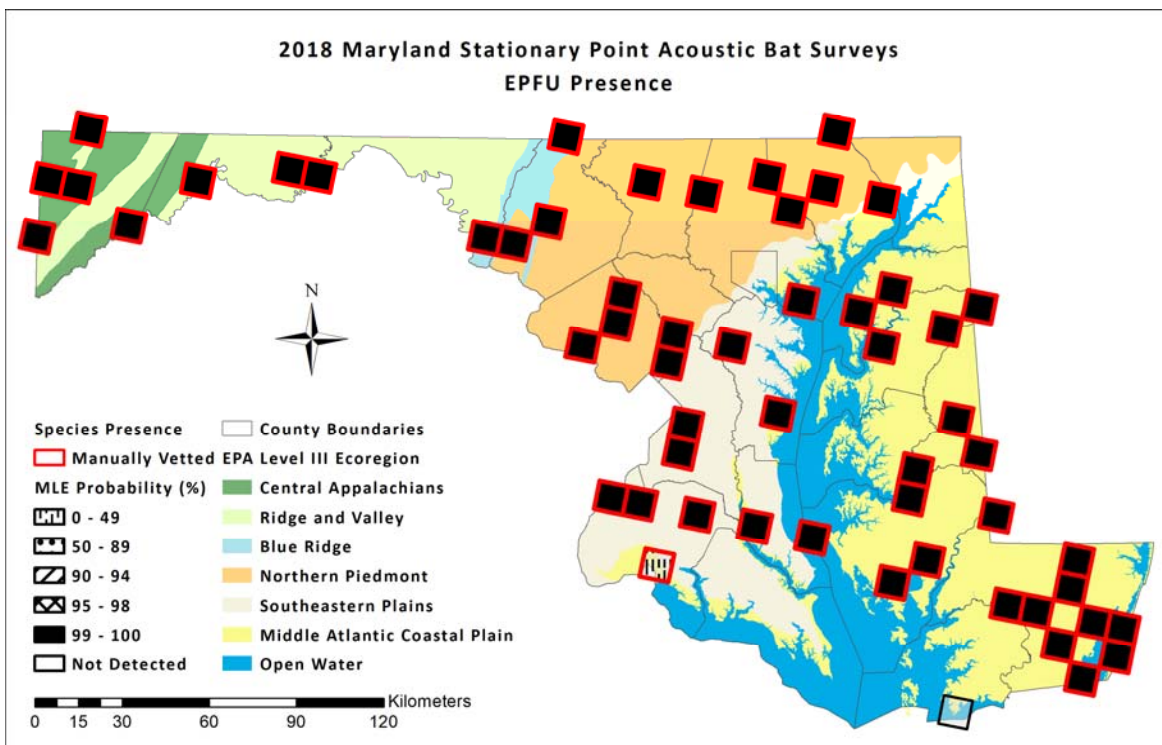


Figure 4. Presence of big brown bat (*Eptesicus fuscus*; EPFU) based on MLEs and manual vetting.

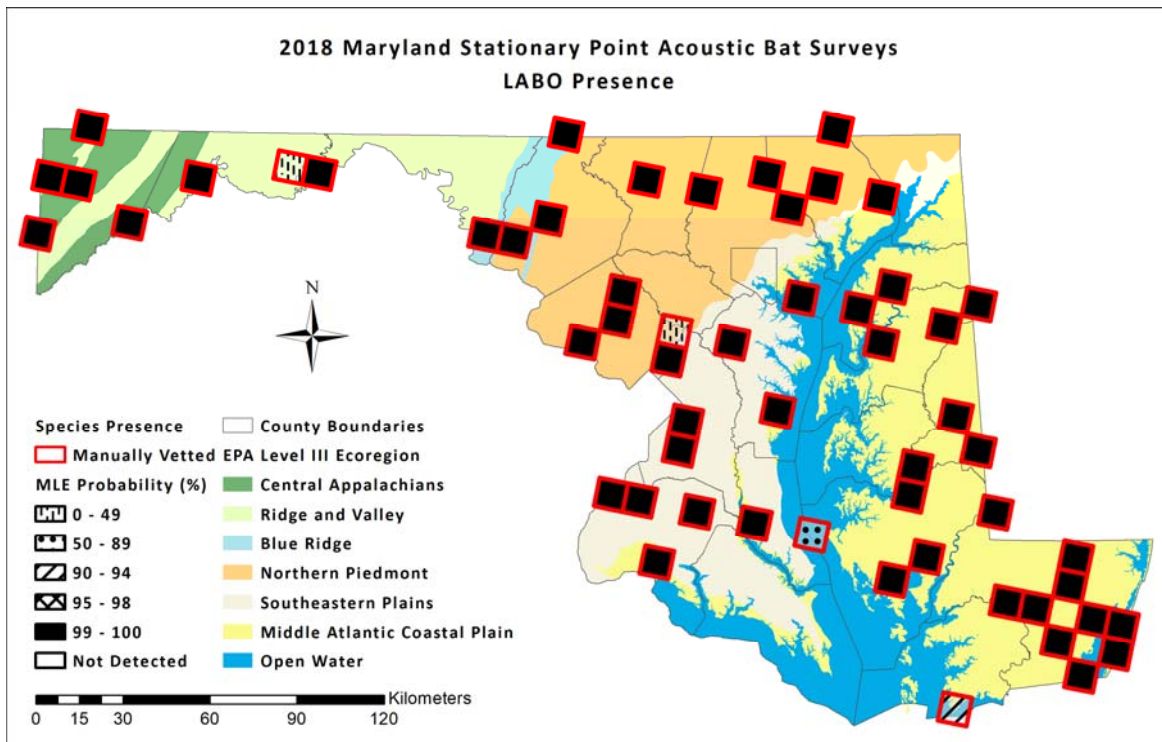


Figure 5. Presence of eastern red bat (*Lasiurus borealis*; LABO) based on MLEs and manual vetting.

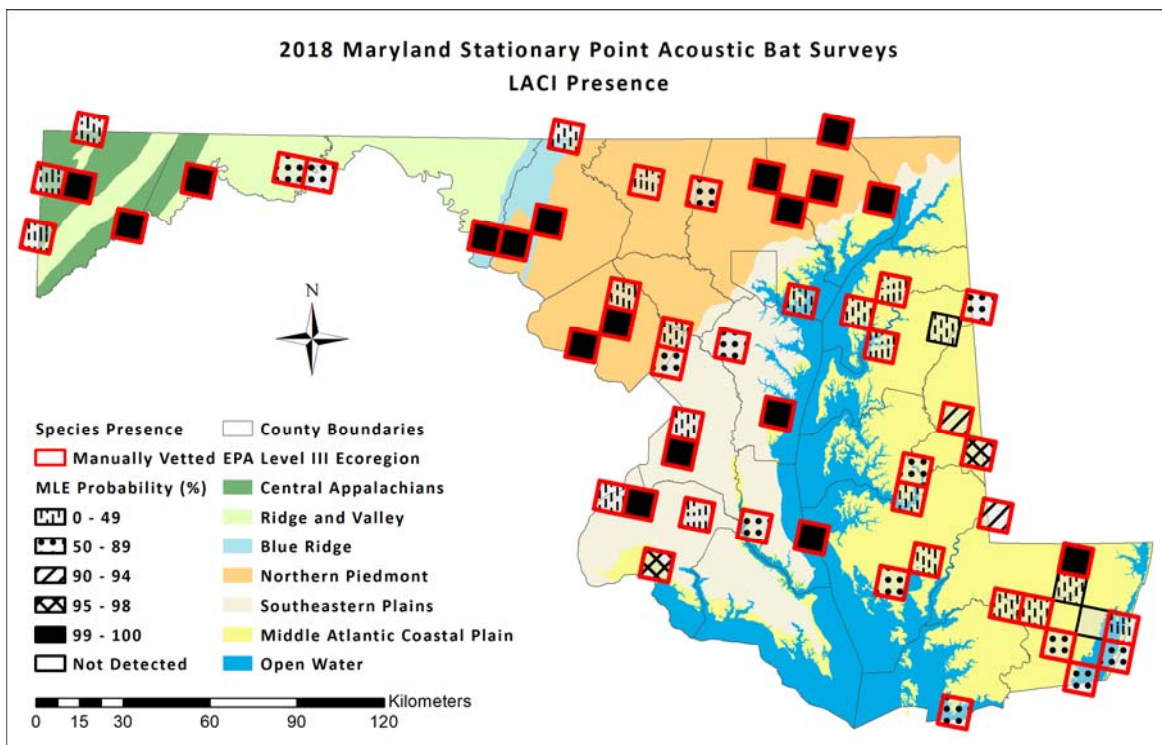


Figure 6. Presence of hoary bat (*Lasiurus cinereus*; LACI) based on MLEs and manual vetting.

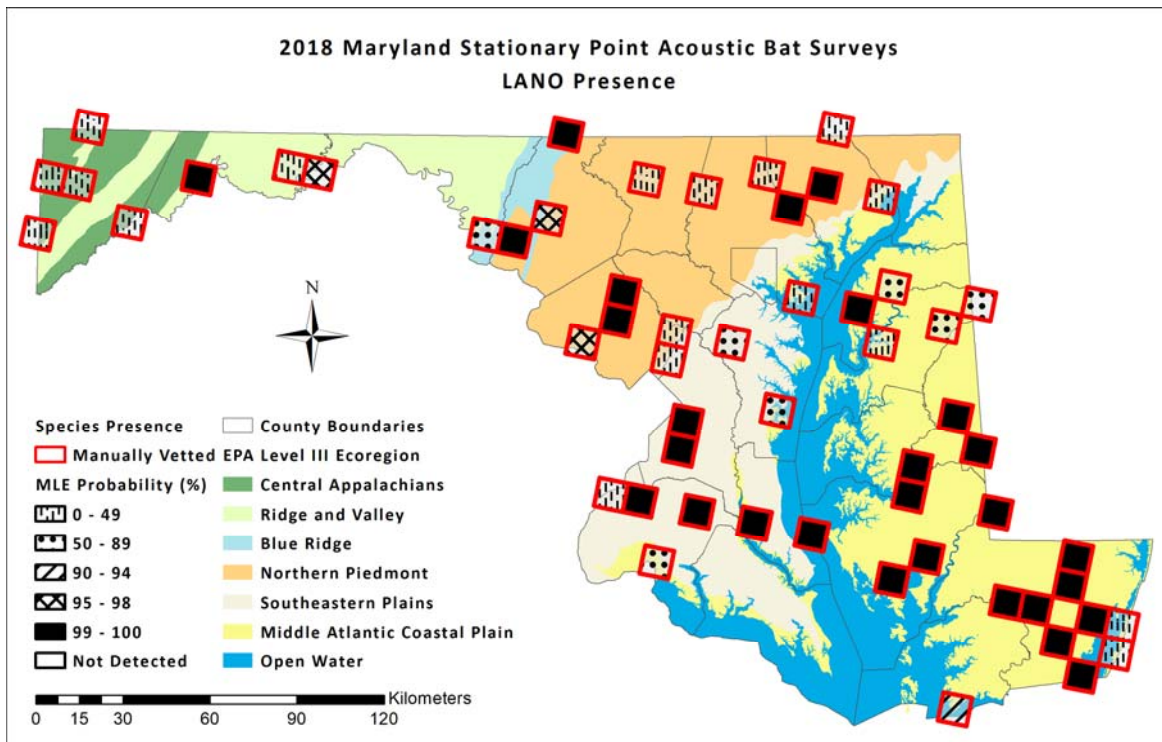


Figure 7. Presence of silver-haired bat (*Lasionycteris noctivivans*; LANO) based on MLEs and manual vetting.

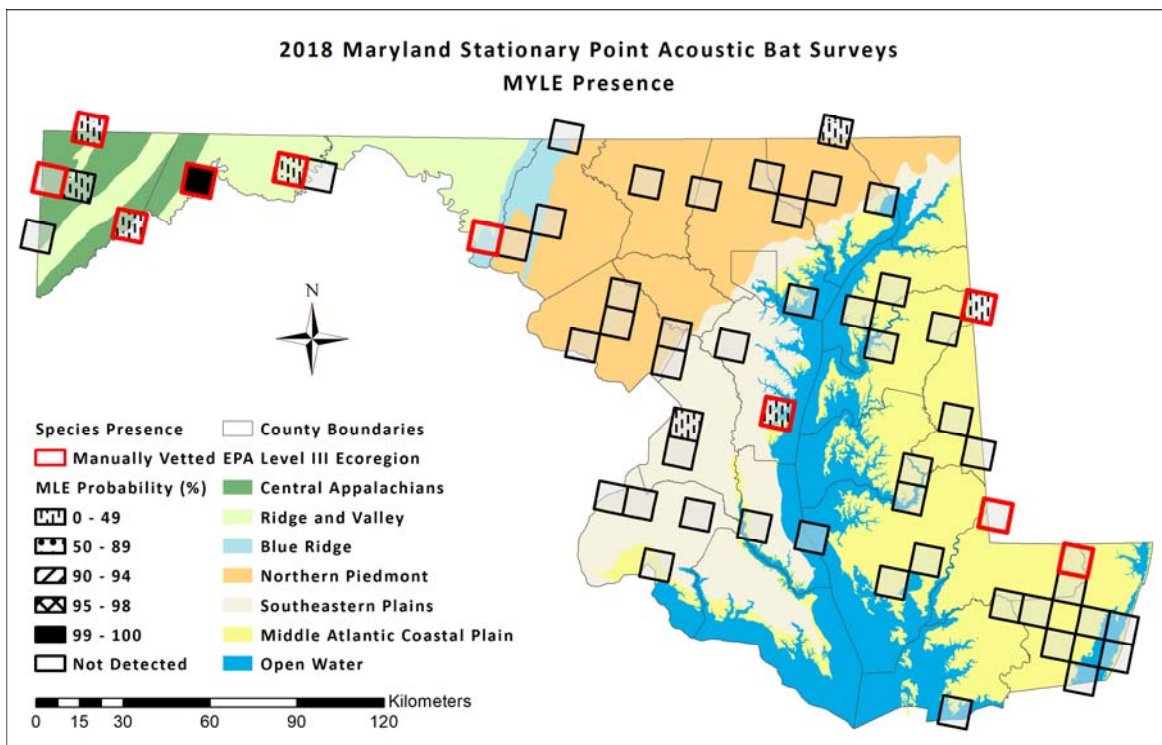


Figure 8. Presence of eastern small-footed bat (*Myotis leibii*; MYLE) based on MLEs and manual vetting.

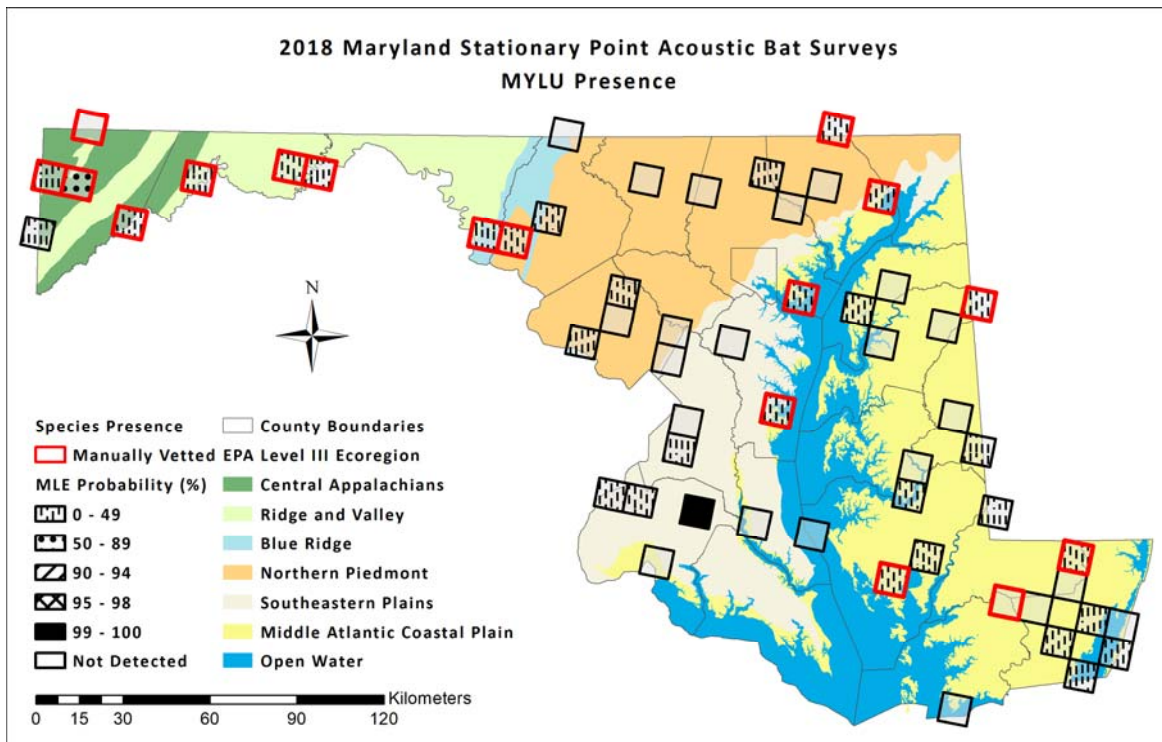


Figure 9. Presence of little brown bat (*Myotis lucifugus*; MYLU) based on MLEs and manual vetting.

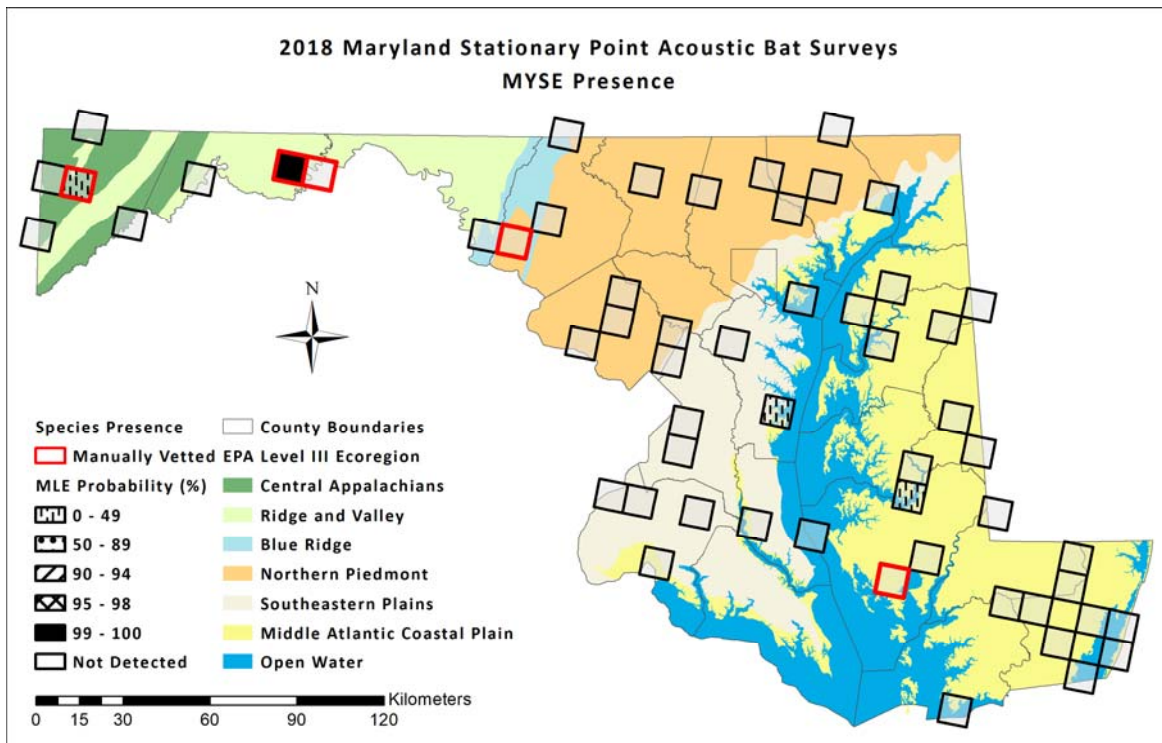


Figure 10. Presence of northern long-eared bat (*Myotis septentrionalis*; MYSE) based on MLEs and manual vetting.

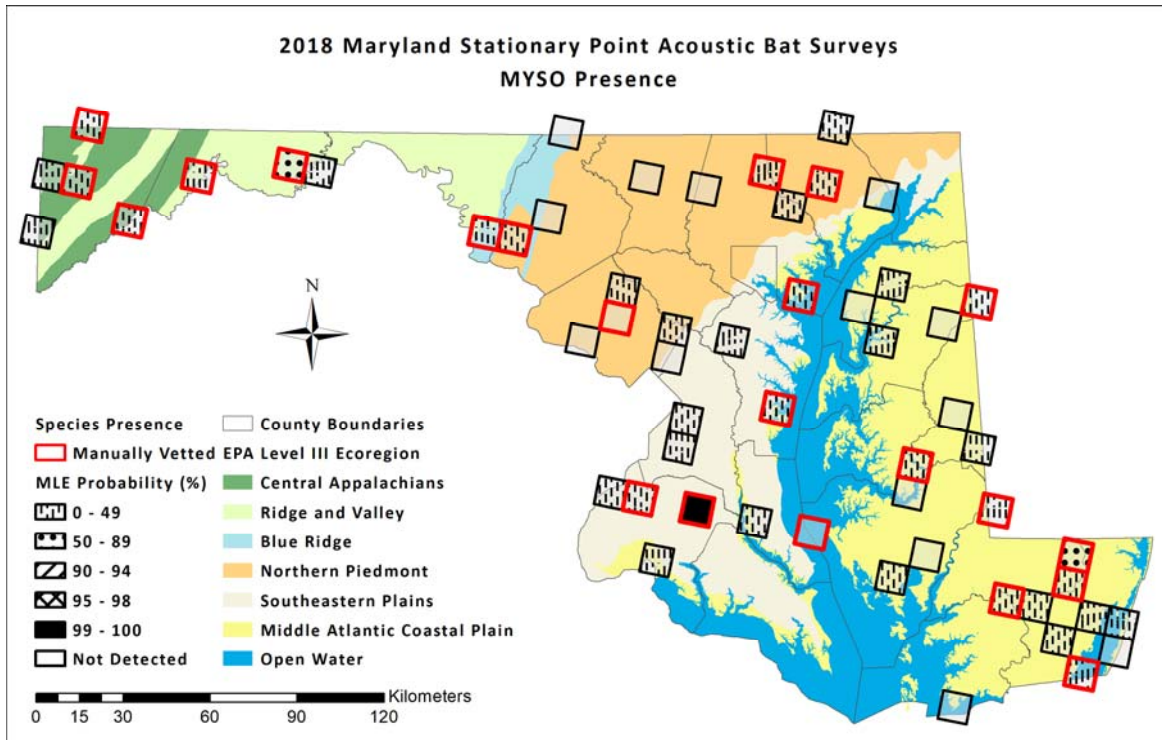


Figure 11. Presence of Indiana bat (*Myotis sodalis*; MYSO) based on MLEs and manual vetting.

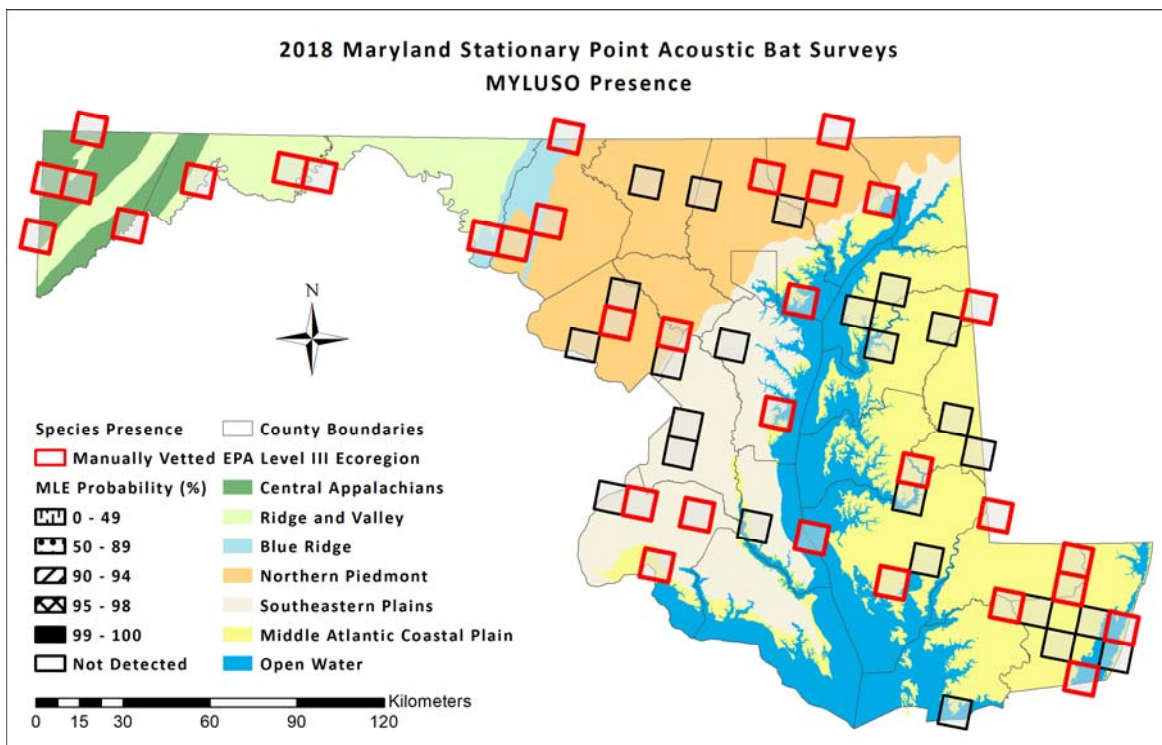


Figure 12. Combined presence of little brown bat and Indiana bat (*Myotis lucifugus* and *M. sodalis*; MYLUSO) based on manual vetting. SonoBat did not calculate MLEs for this combined classification.

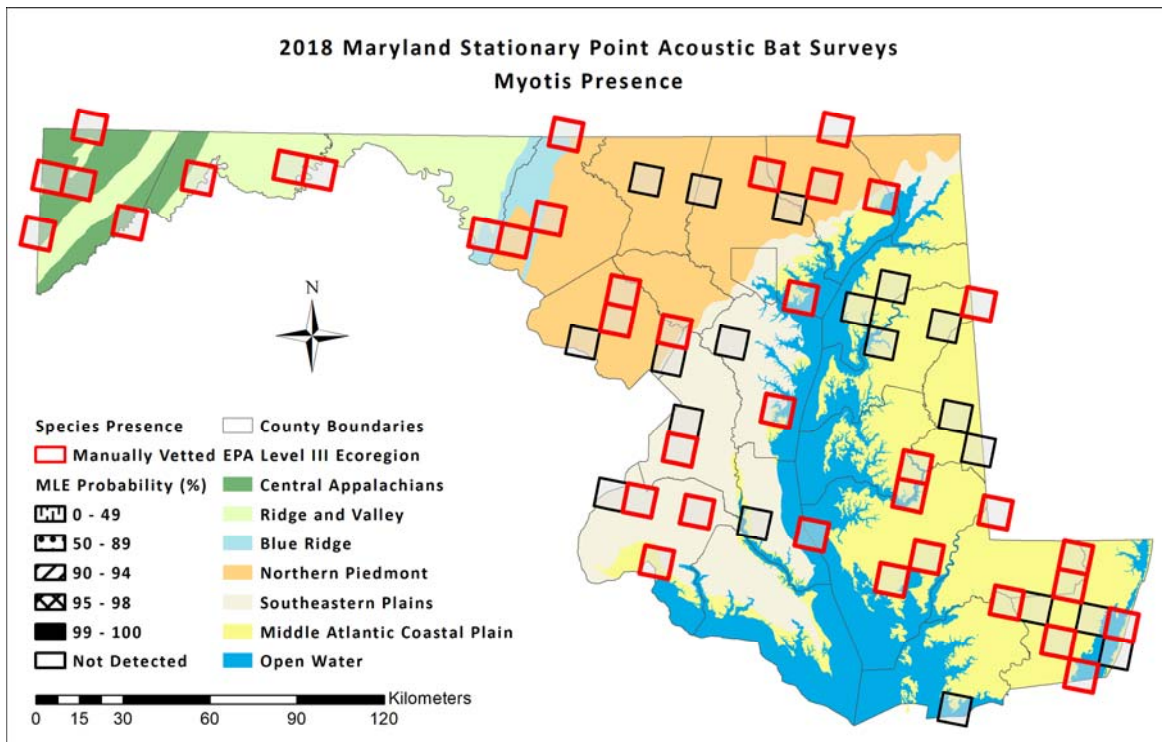


Figure 13. Combined presence of all *Myotis* species classifications and unknown *Myotis* calls based on manual vetting. SonoBat did not calculate MLEs for this combined classification.

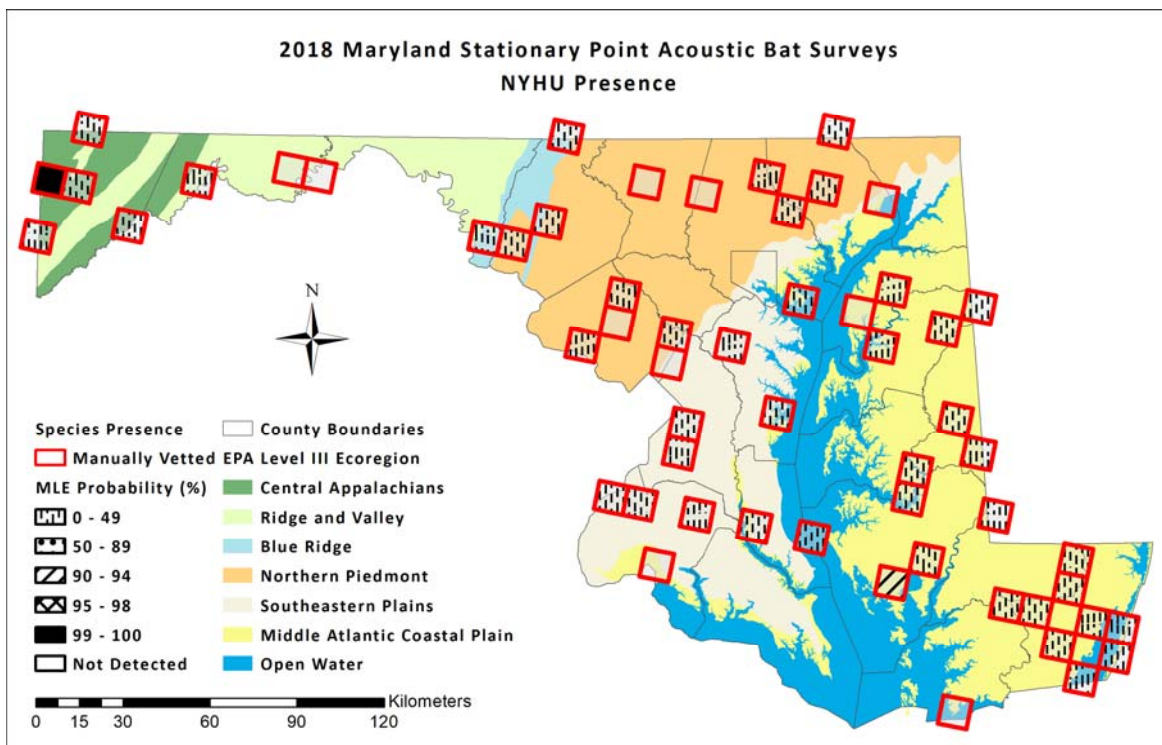


Figure 14. Presence of evening bat (*Nycticeius humeralis*; NYHU) based on MLEs and manual vetting.

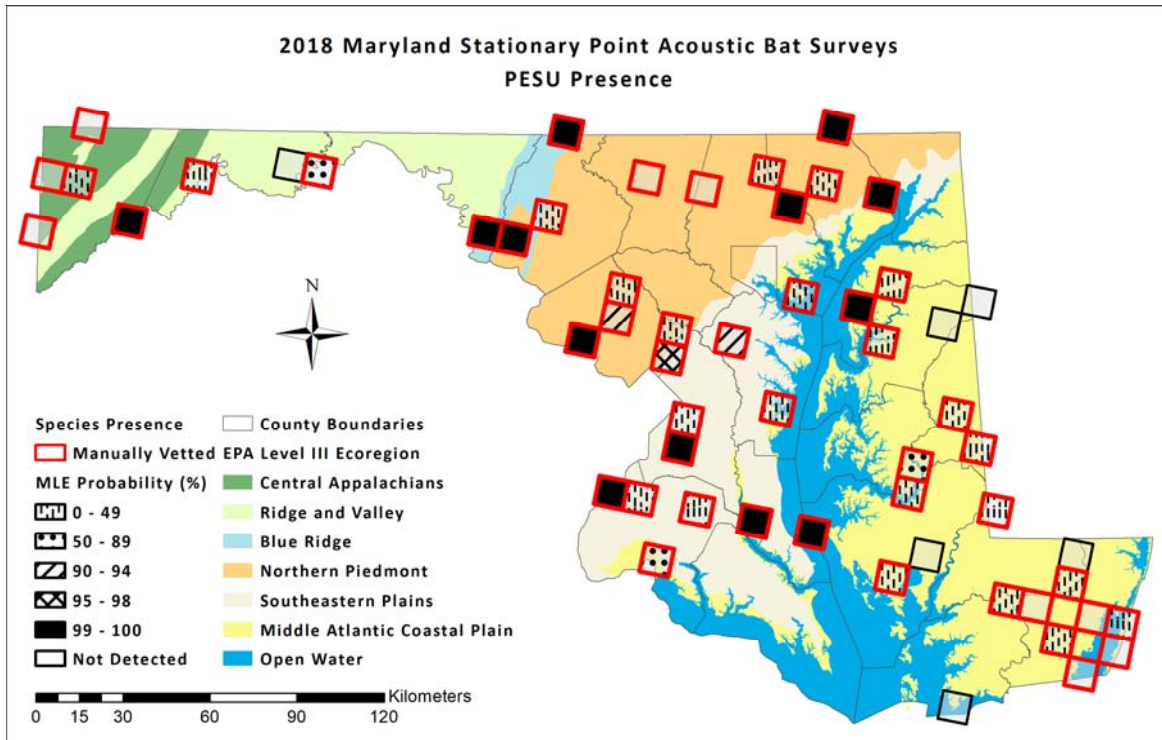


Figure 15. Presence of tri-colored bat (*Perimyotis subflavus*; PESU) based on MLEs and manual vetting.

SonoBat did not include northern yellow bat (*Dasypterus intermedius*; DAIN), southeastern bat (*Myotis austroriparius*; MYAUS), gray bat (*Myotis grisescens*; MYGR), or Mexican free-tailed bat (*Tadarida brasiliensis*; TABR) in the northeastern U.S. classifier, but we did consider that these species may be present when we manually vetted the calls. We did not find any calls of MYAUS or MYGR, but did find calls that most closely resembled reference calls of DAIN (Figure 16) and TABR (Figure 17).

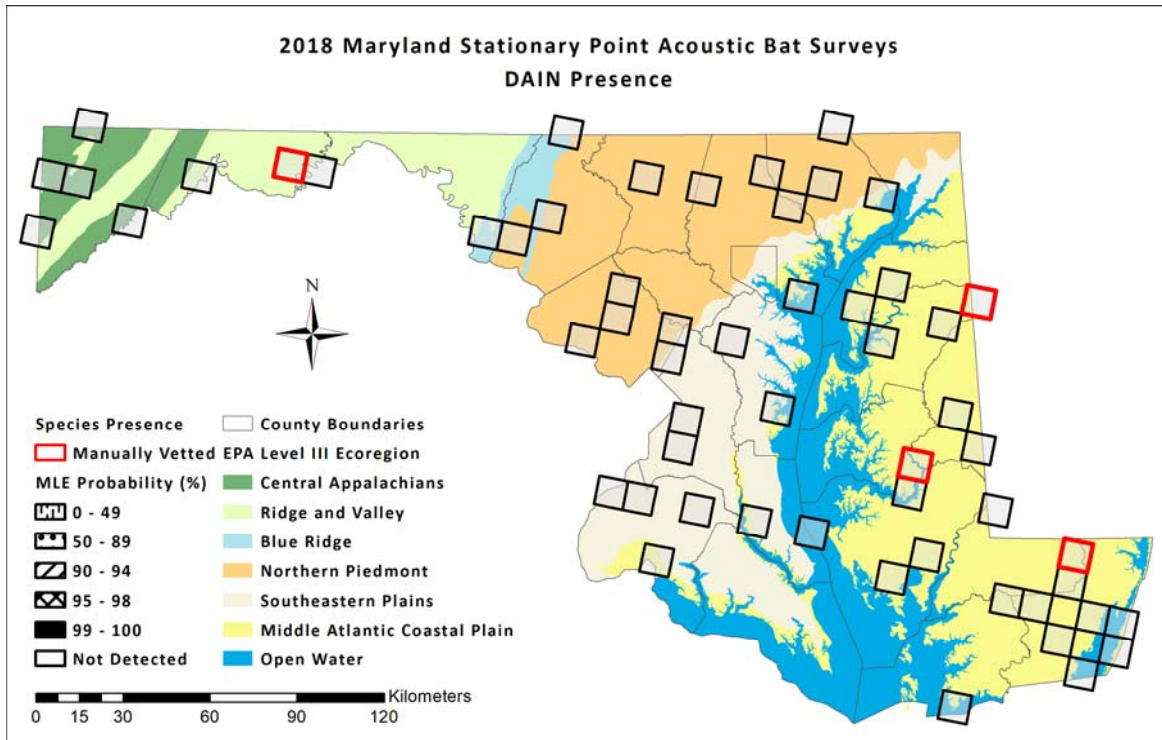


Figure 16. Presence of northern yellow bat (*Dasypterus intermedius*; DAIN) based on manual vetting. SonoBat's northeastern U.S. classifier did not include this species.

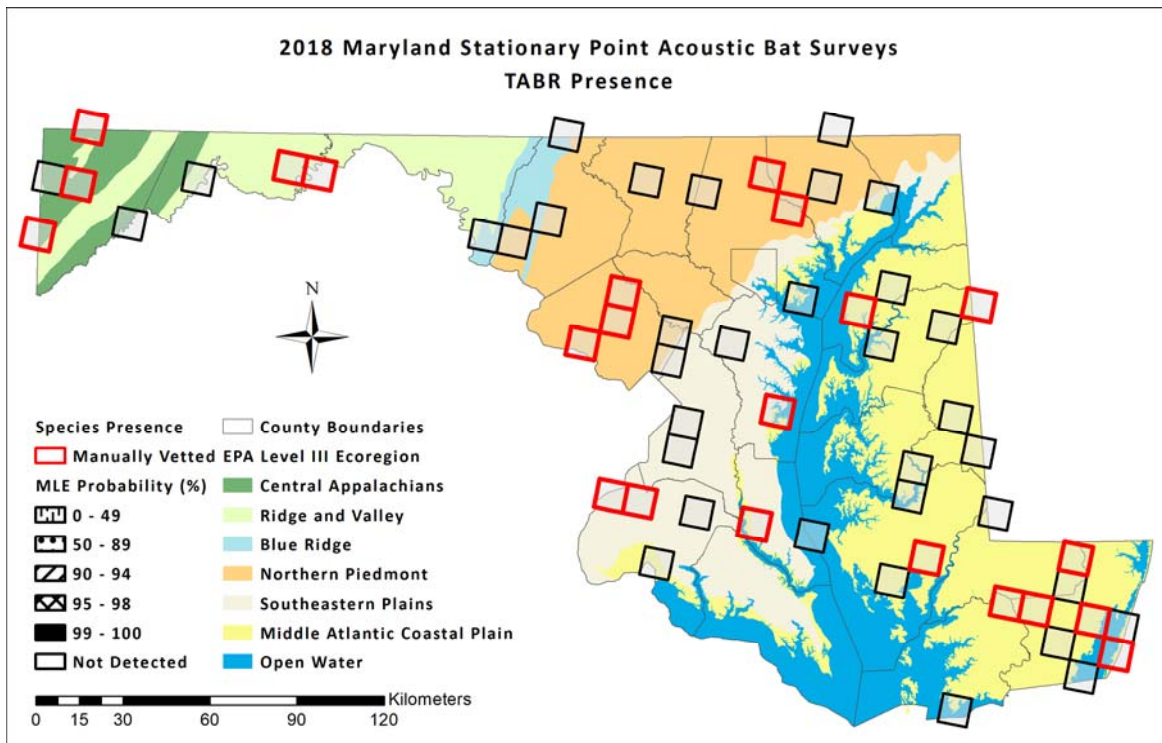


Figure 17. Presence of Mexican free-tailed bat (*Tadarida brasiliensis*; TABR) based on manual vetting. SonoBat's northeastern U.S. classifier did not include this species.

Discussion

Automated bat classification software can be used to reduce time spent processing acoustic data, but some approach should be used to verify presence of species. SonoBat can filter noise, classify calls to species, and calculate MLEs of species presence. In our case, this required just over three days, which is much less time than would be required to manually filter and classify all 178,117 recordings. In contrast, manually vetting the SonoBat classifications required the complete attention of a person for approximately three months. Calls of some species, such as *Myotis*, all of which are listed as critically imperiled in Maryland (Maryland Natural Heritage Program 2016), can be very difficult and sometimes impossible to classify to species, and thus required more time to manually vet than calls of other species.

We found that all three approaches of determining species presence produced different results. Compared to SonoBat accepted species, the MLE approach reduced the number of cells in which each species was present, providing more confidence in the software's results. This approach is consistent and mathematically based, and not influenced by the researcher's skill, bias, or fatigue. Manual vetting may catch calls of species which are missed by automated classification software, and can change species presence results, which in turn could impact management and conservation decisions. For instance, ten species were present in more cells with manual vetting than with even the lowest confidence MLEs. Also, we found presence of DAIN and TABR, which are not in the classifier for the region. However, unlike MLEs, manual vetting is dependent on the researcher, combines qualitative and quantitative evaluations, and may be affected by researcher fatigue and inconsistencies.

Some of the disagreement between MLEs and manual vetting is likely due to the overlap of call characteristics some species have, the high standards SonoBat may have for accepting a species classification, and possibly the current advantage of qualitative analysis manual vetting has over automated classification software. MYLU and MYSO are two species that have very many overlapping call characteristics and often cannot be differentiated, especially when environmental conditions are not ideal for echolocation or recording. This may explain why MYLU was present in one cell with 99% confident MLE, but not with manual vetting. MYSO was present in that cell with manual vetting, so it may have been a misclassification by SonoBat or manual vetting. Researchers often combine these two species for analyses, in addition to EPFU with LANO and sometimes LABO with NYHU, and we will likely do the same. The eastern cell with manually vetted presence of MYSE was also vetted by another biologist to have MYSE presence, but not with 100% certainty (D. Limpert, personal communication, December, 2018). The manually vetted presence of MYLE in the eastern half of the state could potentially be calls of MYAUS, a southeastern U.S. species which is often found in coastal areas and wetlands with similar calls to MYLE, but this would need to be confirmed by physical detections. The presence of two other southern species, DAIN and TABR, may have been misidentified calls of other low frequency species (e.g., EPFU, LANO, or LACI) or social calls of other species. The presence of PESU in most cells was somewhat surprising since it is a species affected by WNS, and there is a chance that some of the detections were actually high frequency LABO calls.

Depending on the research goals and time that can be dedicated, the best approach to verify species presence will vary. Calculating MLEs requires the least amount of time, but may result in a high false-negative rate (i.e., absence of species where they are actually present), as we have shown with higher rates of presence for most species with manual vetting. Thus, a combined approach (e.g., MLEs with 95% confidence and manual vetting of species of interest) may strike the best balance between effort and useful results for making conservation and management decisions. It may also be desired or necessary to reinforce findings from acoustic monitoring with physical detections through mist-netting, and to reduce bias in species presence with false-positive site-occupancy models (Rojas, Loeb, and O’Keefe 2018; Russo, Ancillotto, and Jones 2018).

Future work

Our next steps will be to: 1) manually vet calls of LAIN and TABR with the southeastern U.S. SonoBat classifier, 2) report site level species detections to site managers, 3) work with NABat coordinators to submit our data to the national database, 4) conduct analyses of the data to assist future survey efforts and bat management, and 5) produce final reports on our findings. Planning for additional fieldwork in spring and summer 2019 will also be done in consultation with DNR personnel.

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