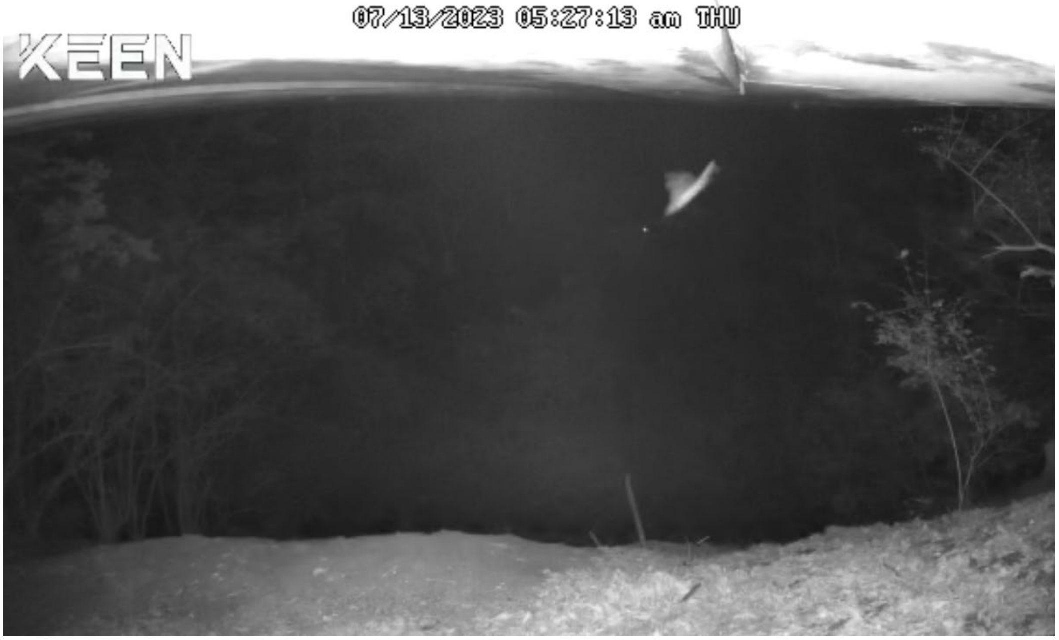
GIS Tools to Identify Bridges with Bats



Prepared by:
Janette Perez-Jimenez, Jacob Koch, Joseph S. Johnson, and Jess N. Kropczynski. University of Cincinnati, Cincinnati, Ohio.

Prepared for:
The Ohio Department of Transportation,
Office of Statewide Planning & Research

Project ID Number: 118513

April 2024

Final Report

Technical Report Documentation Page

1. Report No.	2. Government Accession No.	3. Recipient's Catalog No.
FHWA/OH-2024/06		
4. Title and Subtitle		5. Report Date
Bats and Bridges: Integrating Biology and Cloud-Based Modeling		**April 2024**
		6. Performing Organization Code
7. Author(s)		8. Performing Organization Report No.
Janette Perez-Jimenez, Jacob Koch, Jess N. Kropczynski, and Joseph S. Johnson		
9. Performing Organization Name and Address		10. Work Unit No. (TRAIS)
University of Cincinnati 51 Goodman Drive PO Box 210222 Cincinnati OH 45221-0222		11. Contract or Grant No. **38589**
12. Sponsoring Agency Name and Address		13. Type of Report and Period Covered
Ohio Department of Transportation 1980 West Broad Street Columbus, Ohio 43223		**Final Report**
		14. Sponsoring Agency Code
15. Supplementary Notes		

16. Abstract

Accurately predicting bat use of bridges is an important need for planning of bridge repair and maintenance. However, less than 1% of bridges in Ohio have been surveyed for bats, limiting the inferences that can be drawn from existing data and modelling tools. We developed a method for passive camera surveys of bat use of bridges and reevaluated ODOT's existing tools for predicting bat use of bridges. We were able to create a model that predicts the likelihood that a bridge will be used by bats as roosting habitat. Currently, the data feeding into the model has few positive detections, thus resulting in a model that performs well when determining bridges without bats but leaves room for improvement on determining bridges with bats. With future bridge surveys, the model will improve and the usability of the likelihood predictions will be able to be implemented to aid in bridge management.

17. Keywords	18. Distribution Statement
bats, bridges, cameras, ecology, *Eptesicus fuscus*, machine learning, modelling, monitoring, random forest, roosts	**No restrictions. This document is available to the public through the National Technical Information Service, Springfield, Virginia 22161**

19. Security Classification (of this report)	20. Security Classification (of this page)	21. No. of Pages	22. Price
Unclassified	**Unclassified**	**40**	

Form DOT F 1700.7 (8-72) **Reproduction of completed pages authorized**

Credits and Acknowledgments Page

Prepared in cooperation with the Ohio Department of Transportation
and the U.S. Department of Transportation, Federal Highway Administration

A special thanks to Abagail Dogbe and the University of Cincinnati's IT Solutions Center (ITSC) for their assistance. We would also like to thank our Technical Advisory Committee, Matt Raymond, Matt Perlik, Brittany Trivisonno-Muncy, and Jennifer Spriggs, for their guidance and feedback. Finally, we would like to thank ODOT Districts 1-12, and numerous City and County Engineers throughout Ohio for their cooperation and permission to survey bridges.

1.0 Problem Statement and Introduction

The presence of bats in bridges slated for maintenance or removal can result in project delays and increased costs. To ensure efficient project planning and minimize impacts on bats roosting in bridges, the Ohio Department of Transportation's (ODOT) Office of Environmental Services commissioned the creation of a predictive model in 2020. Built using field surveys for bats at 504 bridges in Ohio, ODOT's model identified variables that could be used to help predict the likelihood that a bridge will be used by bats. Based on these results, the model ranked 44,403 un-surveyed bridges as lowest (n = 1,656 bridges), low (n = 14,577), moderate (n = 18,354), high (n = 8,153), and highest (n = 1,663) likelihood of use by bats. Although this model represents an important first step towards efficient planning, there are several areas where improvements are needed. For example, ODOT's current model is difficult to understand, including numerous statistical analyses and significant predictor variables that sometimes lack clear biological meaning, such as ODOT district. Furthermore, only 7% of un-surveyed bridges were categorized as having either the highest or lowest probability of use, making it unclear how to translate the model into planning. Thus, while ODOT's current model is a significant step forward, further investigation is needed.

The goal of our study was to evaluate ODOT's current predictive model and propose ways to improve its current predictive power and utility. To do so, we set the following objectives for this work:

1. Develop a Method for Sensor-based Passive Surveys
2. Conduct Passive Surveys at a Subset of Bridges
3. Create a New Predictive Model
4. Create a Virtual System to Interact with and Update Data

Objectives 1-2 aimed to determine how to improve upon ODOT's existing tool while taking advantage of the considerable survey data that were used to create the model. Objectives 3-4 aimed to determine if passive surveys could be used to effectively collect more data at bridges to improve available data and, therefore, models. Finally, Objectives 5-6 aimed to reanalyze ODOT's survey data and display the resulting model in a virtual system that is more user-friendly than the current tool.

2.0 Research Background

Bridges can provide critical habitat for bats in Ohio, including federally endangered species such as the Indiana (*Myotis sodalis*) and northern long-eared bat (*Myotis septentrionalis*) (ESI and Lochmueller 2021). The little brown bat (*Myotis lucifugus*), a species currently under review for federal listing, and big brown bat (*Eptesicus fuscus*) are also known to roost in bridges in Ohio. Bat use of critical transportation structures that require maintenance to ensure the safety of the public sets up the potential for human-wildlife conflicts, including delays to important transportation projects when planning fails to account to the presence of sensitive wildlife. Thus, identifying which bridges are used by bats and understanding the environmental factors causing some bridges to be more important than others can help the Ohio Department of Transportation (ODOT) function as effective stewards of both public safety and wildlife. However, bats are highly mobile, cryptic animals with poorly understood ecologies, complicating efforts to understand their use of bridges.

Survey methods typically used to investigate bat use of bridges includes acoustic monitoring (Civjan et al. 2015), visual surveys (Adam and Hayes 2000; Hendricks et al. 2005), identifying bat signs (guano, roost staining, insect parts, etc.) (Adam and Hayes 2000), trapping (Adam and Hayes 2000), and radio-telemetry (Lance et al. 2001). Each survey method has benefits and downfalls. For example, visual surveys can miss bats roosting in weep holes, recessed pockets, or hinge/expansion joints due to the inability to see the full extent of these features (H.T Harvey & Associates 2019). While acoustic monitoring can capture the vocalizations of difficult to see bats, it does not provide information on bat abundance and may introduce ambiguity, since bats passing by the bridge but not roosting in it will also be recorded (O'Shae and Bogan 2003, Russo and Voigt 2016). Depending on the scope of the study, and size of the bridge, different survey methods are appropriate individually or in combination (Civjan et al. 2017).

Because bats are difficult to survey and study, datasets based on a single survey per location may fail to accurately identify which bridges will be used by bats and why those sites are important. This can be seen in ODOT's current predictive model, which despite being large, classified 41% of un-surveyed bridges as having a moderate probability of use. This uncertainty can be produced by survey error (simply missing animals where present), bat use varying during the period of inference (Skalak et al. 2012), and severe imbalance between sites where animals are present compared to places they were not detected (He and Garcia 2009). Furthermore, data can become out of date as bridges age and the landscapes around them change. Given that imperfect detection is unavoidable, it is important to acknowledge that models should be improved over time using multiple within-season surveys (Banner et al. 2018) and continued monitoring of sites such as bridges.

Despite the challenges associated with revealing patterns in the use of bridges by bats, several studies provide an important starting point for understanding this phenomenon. For example, a few reports indicate that bridge structure type and surrounding habitat are the most notable features when summarizing bat presence. The most prevalent finding is that bats tend to be observed more frequently using concrete bridge structures over other materials such as steel or wood (Keeley and Tuttle 1999; Adams and Hayes 2000; Gore and Studenroth 2005; Hendricks et al. 2005). It is hypothesized that concrete offers ideal thermal characteristics for roosting bats, since it can absorb and hold heat to buffer fluctuations with ambient temperatures thus retaining a more consistent thermal profile (Adams and Hayes 2000). Other notable bridge structures of importance include the girder structures, often present in I-beam bridges, and box bridges, which are speculated to offer shelter from the elements (Gore and Studenroth 2005; Phares et al. 2018).

Additionally, bats are more likely to use bridges that are close to riparian and woodland habitats (Hendricks et al. 2005; Jackson and Cleveland 2007; Phares et al. 2018). While some influential features have been consistently identified, others have inconsistent thresholds of importance documented in literature.

The results from ODOT's existing model (ESI and Lochmueller 2021) include variables that have inconsistent thresholds of importance in previous literature, such as bridge age, deck area, and membrane type. Variables such as bridge age might have been found highly important in some studies, while in other studies the same variable was only marginally important. Older bridges are likely to have some degree of deterioration, which tends to offer a more textured surface for gripping, may introduce new crevices for roosting, and in general increases the opportunities that bats have to find the structure. Although there is biological evidence to support the use of older structures, there has only been marginal support for this variable to be important for bat presence (Gore and Studenroth 2005; Betkas et al. 2018). To our knowledge, bridge area has not been assessed elsewhere, however similar proxies such as bridge length and width have been assessed and found to also have marginal support (Betkas et al. 2018). Thus, although our current understanding of the bridge features that are important to bats in Ohio is not without a foundation in the existing literature, the importance of variables such as transportation district (ESI and Lochmueller 2021) suggests our current state of knowledge may be biased and in need of further investigation.

3.0 Research Approach

To meet our goal of evaluating ODOT's current predictive model and proposing ways to improve its current predictive power and utility, we established a distinct approach for each of our six objectives.

3.1 Assessing ODOT's Current Predictive Model

To assess ODOT's current model, we conducted a review of the survey data the model was built upon, met with its authors (ESI and Lochmueller 2021), and conducted a literature review of approaches to modelling ecological data. In reviewing the existing data, we looked for potential sources of bias, such as the spatial and temporal distribution of sampling effort, the proportion of observations where bats were present compared to absent, and model applicability given the data collected. These characteristics of a dataset can help determine the best approach for modelling presence-only data, such as ODOT's bridge survey data. In meeting with the authors of ODOT's current model (ESI and Lochmueller 2021), we discussed the decisions that they made when collecting and analyzing their data. We gathered this information to understand the information presented in their report to fully realize the limitations of their rating system. As with any modeling approach, understanding the limitations and checking the assumptions are important steps in verifying that the modeling approach is appropriate.

3.2 Provide recommendations for Improving ODOT's Predictive Model

We evaluated a variety of modelling approaches to find the most appropriate given the data that ESI and our team collected. Both datasets contain presence/lack of detection data and do not attempt to quantify the number of individual bats present at all sites. Given the nature of these surveys, presence/absence was the most feasible and accurate data collection method, however this often provides inadequate for a variety of modeling techniques. Many modeling techniques exist that have potential to interpret presence/lack of detection data, select important predictor variables, and allow for potential interactions between variables. A commonly used method is a generalized linear model (GLM) (Carlos-Júnior et al. 2020). This modeling approach allows for testing presence/lack of detection data; however, there are limitations. Firstly, GLM modeling approaches have the potential to produce overfit models that do not accurately assess the importance of variables tested. Overfitting can be caused by lots of predictor variables, given the extensive number of variables that we wanted to assess, and the inadequate number of positive detections we ruled out GLMs as an appropriate modeling tool. Additionally, this modeling tool would require that we identify potential relationships between predictor variables and transform the data appropriately to reflect this. While a few relationships could be reasonably conceived, many remain unknown to us. Occupancy modeling was another tool that was considered and quickly ruled out given the nature of the data. This approach handles imperfect detection well; however, it required count data at all sites instead of presence/lack of detection data. Given that GLMs and occupancy models did not fit the data previously collected for ODOT (ESI and Lochmueller 2021), we decided to use a random forest modeling approach. Random forest is well-suited for investigating the importance of a large number of predictor variables, such as the case with ODOT's data. Furthermore, since this modeling approach is resistant to overfitting it preserves the relationships between the predictor and response variables and control for model complexity.

Random forest is a type of machine learning approach that is a non-parametric method of supervised learning. We use an iterative-based approach to building the most parsimonious decision trees with the data it is given. For our analysis, we ran 3,000 iterations or "trees" each built to explain the variance in the data given a set of predictive factors. This modeling approach has many benefits, the three main reasons we selected this approach were: 1) the lack of assumptions about the data; 2) it can handle both non-linear, linear, and interaction relationships among multiple predictor variables; and 3) this method can handle a larger ratio of observations to data collected since it corrects for over and underfit data. The data was optimized by removing any variables that had a percentage of variation that was less than 0 and removing any predictors that had less than 0.5 increase in mean standard error to the model. The response variable used was presence of bats, a binary metric of bat presence observed per bridge per day, regardless of the method of verification (visual, recording, DNA from guano).

A critical step in evaluating presence/lack of detection data is in the specific language used to communicate the results. While nominal, the language used in predicted results must communicate the precision and accuracy of the information. Given the data collected, honest parameters must be put in place to understand the results and to ensure they can be responsibly interpreted. The higher quality data that is available without bias, the more certainty you can provide. The data that we collected does not discern between occupancy and detectability with a binary presence/lack of detection metric. Additionally, these data occurrence values must be interpreted as a ranking of occurrence because the surveys provide data where the probability of detecting species is positively correlated to species occurrence (Guillera-Arroita et al. 2015).

3.3 Develop a Method for Sensor-based Passive Surveys
To augment traditional visual surveys of bridges for bats, we compared six wildlife/security cameras to select a model that best suited our application: Moultrie Mobile Edge, Blaze Video, Reveal X-Pro 2, StealthCam, Reconyx Hyperfire 2, and Keen Reolink. These cameras were selected for comparison based upon a review of products available on the market that were capable of recording video in low or no light, have a relatively fast trigger speed, have adequate resolution, have an internal battery life of 2 weeks or more, and priced under $400. Although we did not limit our consideration to cellular cameras, we prioritized our search for cameras that could send live videos through a mobile application to monitor for potential theft.

We compared the ability of each camera model to detect bats by placing the cameras outside a building containing a maternity colony of little brown bats. Cameras were placed outside the roost during 3 nights in April of 2023. Cameras were placed 12 meters away from the building, pointing towards the known emergence location. After a period of high activity, we compared the activity that was captured on each respective camera and adjusted camera settings, if appropriate, to find the optimal settings. Additionally, trigger speed was evaluated by timing known movement in front of the camera to the time each camera recorded. It became apparent from field tests that the IR lights built into the camera models were not sufficient to clearly illuminate bat activity for image capture. While a few camera models were able to capture movement, none provided images clear enough to decipher if the animal recorded was a bat or another flying nocturnal creature. Field testing was repeated using supplemental IR lighting to find new optimal camera settings that produced clearer images and video captures.

3.4 Conduct Passive Surveys at a Subset of Bridges
Once we determined which of the six camera models would be best suited to passively recording bats under bridges, we deployed cameras in the field to collect additional data for the predictive model. Prior to deployment, we created a random sampling strategy to establish a representative sample of bridges to assess the likelihood of bat presence. We omitted sites that required a snooper, were culverts, has tolls, or bridges over major highways and railroads. These omissions were made largely to allow for safer access to these sites. We omitted culverts because our camera mountings were not appropriate for culverts. We used R Studio (2020) to randomly select bridges from each of the 12 ODOT districts, for a total of 60 potential

survey sites. Due to limitations in the field season, only 52 sites were visited between June and July 2023 to determine if the site was suitable for camera deployment. We determined that 27 sites were suitable for camera deployment. Visual inspections for bats occurred at 15 of the 52 sites when it was possible to inspect the full bridge on foot. In some cases, a partial inspection occurred at the area accessible from where camera was deployed, but it was not recorded as a full human survey in our data. A site was considered suitable for camera deployment if there was cellular service, if the area under the bridge could be accessed safely, and if flooding was deemed unlikely to occur. Cellular service was important because the camera model selected for our application (see Section 4.3) required cellular communication with a mobile application. Locations prone to flooding were avoided to protect the equipment from water damage.

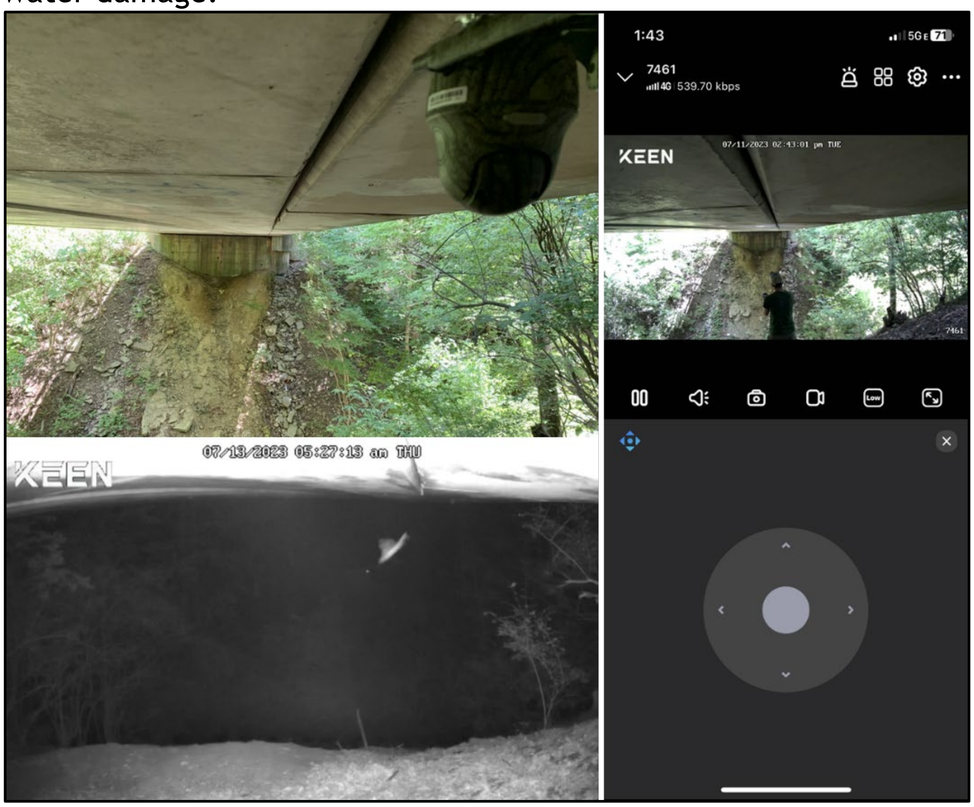


Figure 1. Example of a Keen Reolink camera deployment in the field. Top left: View of a camera attached to the bottom of a bridge in Warren County, Ohio, using mounting tape. Right: screenshot of the Reolink mobile application showing how the cameras can be aimed and armed using a trackpad in the app, allowing for remote control and viewing. Bottom left: still image from a video of a big brown bat entering an expansion joint under the bridge shown top left.

The camera that we chose for our study was the Reolink Keen Ranger. This camera allowed us remote access to video streaming of the camera, allowing the user to adjust, aim, and capture video remotely using an application, while also storing the data captured to the cloud (Figure 1). The camera was also equipped with night vision and an IR light to help capture nighttime video. Cameras were paired with an additional battery powered external IR light to boost the distance so that clear images of bats could be observed as they enter and exit bridges. We deployed one camera at each bridge, with the exception of two sites. Cameras were placed at locations that appeared suitable for bats and were accessible. Only one camera was placed at most bridges, but at two bridges where bats were seen during camera deployment, we placed two cameras at two different locations/vantage points to ensure that we would capture the bats on camera in order to test the equipment. The cameras successfully recorded the bats at these locations. The cameras were secured underneath the bridges using an adhesive putty, tape, and chains with padlocks (site dependent) that were easy to install and remove with no impact on the structure or the ecosystem.

Cameras were deployed in the field for an average of 10.2 ± (5.5 SD) days (range = 1–23 d). To store captured videos during the survey, the Reolink cloud storage was utilized. The cloud storage allowed cameras to push videos to the cloud as they were captured and allowed us to view them in a mobile dashboard that was provided through the Reolink mobile app (Figure 1). Once videos were stored to the cloud and we had completed our survey, we were able to download and store them in the UC OneDrive cloud storage for use in the Virtual System.

3.5 Create a New Predictive Model

Based on our review of the data and literature (see Sections 4.1 and 4.2), we elected to combine the results of our camera and visual surveys with ODOT's previous data (ESI and Lochmueller 2021) into a new predictive model. We used the variables in Appendix 1 to generate a new predictive model using random forest. The variables in Appendix 1 were extracted from various sources and encompass three conceptual categories: environmental, bridge structures, and disturbance. Environmental variables describe the natural area surrounding the bridges that bats may utilize as foraging habitat, roosts, or cover from predation. Bridge structure variables describe the roosting structure that may influence the thermal profiles, texture, and ability to hide during daylight hours. Disturbance variables describe potential negative impacts that may influence bats using or abandoning a structure. These categories include variables that were included in ESI's model in addition to variables that we deemed potentially explanatory of bat presence within the structures. Variables were extracted from the ODOT Transportation Information Mapping System (TIMS) and U.S. Geological Survey (USGS) datasets (2021).

3.6 Create a Virtual System to Interact with and Update Data

In addition to improving the analysis behind ODOT's predictive model, we sought to improve upon its usability and lifespan by creating a virtual system to allow users to interact with the model results. Broadly, we developed this system, which we named **BATMAP**, to meet what we perceived as three needs of the user: 1) provide a secure, remote web interface for connection; 2) provide a map-based display that is easier to use than ArcGIS software; and #) provide a means for the addition of new data.

To meet these needs, we first architected a solution based on the requirements of ODOT. Those requirements being that the application must be able to run and use the architecture that is approved by ODOT IT. The first requirement was that our application utilize either C#, Angular, or Bootstrap as the programmatic language for the application. The next requirement was that the application utilize Oracle 12C as the backend database, this will allow it to tie into the existing data structure storage architecture that ODOT uses. The third requirement was that the application must utilize Windows Server for the web server in our application. Finally, if our application utilized Unix, we would be required to use Red Hat Linux as the Linux distro for our application. These requirements provided a baseline for designing a system that ODOT could manage and integrate given their internal IT standards. We envisioned the solution as a web-based virtual dashboard that would connect with a back-end database and that would store a link to the video files that are stored in the OneDrive cloud storage, visual survey data, and other reports that the system has captured and stored for future analysis and data visualization (Figure 2). This would provide the users the ability to batch upload data, as well as view visual pinpoints that provide a wealth of information to the user about previous studies that have occurred at that location.

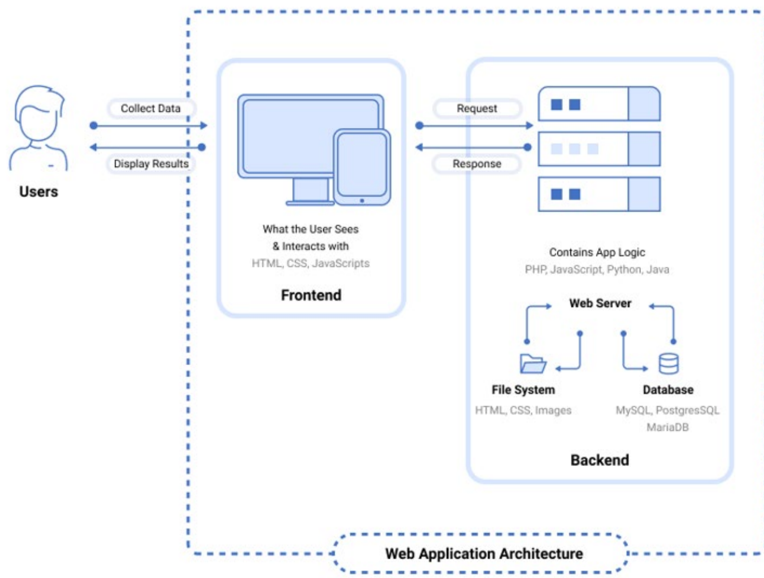


Figure 2. BATMAP frontend and backend architecture. In BATMAP, users interact with the frontend of the system to request or to push data into our backend, which houses our file system and database for the web server. The backend handles data storage and the computation user request through different Java scripts, HTML, or CSS script request. BATMAP's file system manages all other stored details that the backend holds to present visualizations for the frontend.

We designed BATMAP to allow users to both visualize bat survey data in a map-based view and to display meaningful metadata about any bridge a user might be interested in querying. BatMap includes both a map-based view and data about bridges. We have designed this tool with a database that uses data from our analysis and that of ESI and Lochmueller (2021), and we have populated it with this data. Finally, we made BATMAP so that it could be reached remotely through the Internet and housed in the UC cloud space or delivered directly to ODOT.

4.0 Research Findings and Conclusions

4.1 Assessing ODOT's Current Predictive Model

ESI used bat survey data provided by ODOT for 21 structures (bridges and culverts) to conduct an initial analysis for bridge selection based on deck area, distance to stream, amount of forest within five miles, primary construction material, type of structure and presence or absence of a concrete deck (Table 1). From this initial stepwise binomial general linear model (BGLM) analysis, they derived three categories of bat suitability (high, medium, and low) which they used to select a minimum of 50 bridges in each category out of a total bridge inventory of 44,403 (Table 1). During the summer of May 2020, 504 bridges were surveyed across Ohio for bat presence.

Surveys were done with visual inspection, unmanned aerial vehicles (UAV; “drone”), and acoustic surveys for presence/absence data. A subset of 18 sites were selected for species confirmation by using a DNA analysis from guano. Bats were found at 17% of sites with high probability, 0% of moderate probability and 4% of low probability. Based on field assessments of bridges, they modified their initial BGLM into what is referred to as a “step-down” model to add an additional set of moderate probability bridges, thus increasing the percentage of bats to 7% at moderate sites (Table 2). This “step-down” model is a combination of the BGLM and their personal observations to generate a model which is functionally similar to a dichotomous key (D. Sparks, personal communication, February 6, 2023).

Table 1: Summary of results of 2020 surveys by ESI after initial binomial generalized linear models (BGLM) and after adding survey sites.

Initial Rank	Number Sampled	Bat Positive Bridges	Percentage of Bridges with Bats
Initial Targeted Bridges			
High	133	22	17%
Moderate	40	0	0%
Low	56	2	4%
Additional Bridges			
Moderate	315	23	7%

The results of their findings were assessed using both univariate (Pearson’s Chi-square test) and multivariate (Generalized Linear Model) approaches to assess bat likelihood of presence based on variables that were deemed the most important. The results indicate that there is a relationship with probability of bat use based and ODOT District, type of bridge, bridge material, and type of membrane (Table 2). The most important type of bridge material is concrete. Most notable was the preferred bridge type, which were beam and box beam bridges which have also been observed in similar studies. Membrane type and ODOT district were noted as having significant relationships with bat presence but have not previously been evaluated prior to this study to our knowledge.

After evaluating the importance of variables associated with bridges where bats were detected, they evaluated all bridges that were surveyed with the aim of explaining the variation in bat use across the bridges. They used a series of stepwise regression models to evaluate all variables, structural and design variables, nonstructural variables and environmental variables. The variables that were statistically significant from these regression models are summarized below:

- ODOT District (District 8) was positively correlated with bat presence
- Year Built (newer bridges) was positively correlated with bat presence
- Material (metal) was negatively correlated with bat presence
- Foraging habitat within 0.25 mile was positively correlated with bat presence
- Deck area (larger) was positively correlated with bat presence

After reviewing the results of the stepwise GLM they modified the predictions of these models into a final "step-down" model that incorporates field observations with statistically significant predictor variables to make their final assessment regarding bat likelihood of using all 44,403 bridges.

Table 2: Results of ESI's Pearson's Chi-square test evaluating the likelihood of bat presence based on select bridge variables.

Variable Tested	X2 Value	Degrees of Freedom	p-value	Significant Relationship?
ODOT District	34.31	11	< 0.01	Yes
Type	18.33	6	< 0.01	Yes
Material	11.81	3	< 0.01	Yes
Description	8.96	6	0.18	No
Type of Service Under Bridge	11.03	6	0.09	Trend
NBI Rating	5.04	3	0.17	No
Type of Membrane	23.38	6	< 0.01	Yes

The final "step-down" model offers insight regarding important predictive variables while setting the groundwork for subsequent studies to make the model broadly applicable to all current and future bridges. The models that preceded the "step-down" model include a series of eight binomial GLMs. The following four models resulted in intercept p-values that were >0.05 which means that we cannot conclude that the predictor variables affect the response variable with statistical significance:

- *glm(formula = Bats ~ Type + Material + Description + Deck Area + Membrane + National Bridge Inventory Rating, family = binomial)*
- *glm(formula = Bats ~ ODOT District + Year Built + Type of Service Under Structure + National Bridge Inventory Rating, family = binomial)*
- *glm(formula = Bats ~ ., family = binomial)*
- *glm(formula = Bats ~ ODOT District + Material + Type + Deck Area + Lanes Under Structure + Streams + Forest within 0.5 miles + Foraging habitat within 0.25 miles, family = binomial)*

The three next best GLMs had predictor variables that were focused on structural design, nonstructural variables, and environmental variables, and are as follows:

- *glm(formula = Bats ~ Material + Deck Area)*
- *glm(formula = Bats ~ ODOT District + Year built)*
- *glm(formula = Bats ~ Distance to Stream + Foraging Habitat within 0.25 miles)*

From these models five variables were identified as statistically significant for predicting the likelihood of bat presence: deck area, foraging habitat, material, year built, and ODOT district. While these variables were the most significant statistically, the model predictions for bat probability were not consistent with the surveyors' observations. As a result, ESI created a new model that used these variables and field observations to make predictions, they called this theoretical model a "step-down" model. Since the model required an ambiguous amount of human guidance to specify bat presence it is not scalable nor repeatable and no longer applicable to the newly created bridges since the study was conducted.

4.2 Provide Recommendations for Improving ODOT's Predictive Model
We evaluated modeling tools and found that ODOT's Predictive Model needed improvement in the following areas: 1) inclusion of additional biologically relevant variables 2) ability to be reproduced and inclusive of newly collected data and 3) transparent interpretation of model performance. For these reasons, we chose to use the random forest modeling approach to interpret the likelihood of bat presence at Ohio's bridges. Details for our new modeling tool can be found in Section 4.5.

4.3 Develop a Method for Sensor-based Passive Surveys
After testing, we determined that, given the distance between an individual camera and potential bats in flight, a supplemental IR light was needed to ensure that cameras would trigger and produce videos where bats could be discernable. With the addition of a supplemental light, we selected a surveillance camera for our passive surveys (Keen Reolink). Results from our pilot studies are summarized in Table 3. We elected to go with the Keen Reolink due to the purchasing availability at the time of the study, in addition to the ability to transmit audio through the unit in case of theft.

4.4 Conduct Passive Surveys at a Subset of Bridges
We surveyed 27 bridges using Keen Reolink cameras with multiple days of observation at each bridge totaling 306 days of camera monitoring. Three of these 27 locations included sites where ESI and Lochmueller (2021) surveyed for bats in their research. We also conducted full visual surveys at 15 additional bridges that we deemed unsuitable for cameras. Thus, the present research adds survey data to 52 bridges, including 49 not previously surveyed. In the two instances when bats were present during camera deployment, we pointed the cameras towards the bats and successfully recorded them. We recorded bats on 9 days (2.9% of all days where cameras monitored bridges). This included recordings at 5 different bridges (18.5% of all bridges where cameras were deployed). Two of these 5 bridges were sites where ESI and Lochmueller (2021) previously documented bats. No bats were seen at the 15 sites with full visual surveys. Full visual surveys could not be conducted at the two bridges where bats were seen during camera deployment. Three new bridges with confirmation of bats have therefore been added to ODOT's database. Recordings at these bridges included video observations of bats entering the bridge or exiting the bridge. We did not record video or see any evidence of bats at the remaining 37 bridges. In some circumstances, cameras were triggered by other wildlife or humans. The passive nature allowed us to capture wildlife in their natural habitat without interfering, allowing us to see the natural behavior of these animals. Larger mammals such as deer, rabbits, squirrels as well as smaller mammals such as mice or amphibians such as frogs, many bird species, and reptiles such as turtles were able to

trigger our camera sensors. Human interference was also a problem, leading us to adapt our strategy on how we camouflage and deploy these sensors. To minimize the potential for human interference, the cameras were hidden in natural features or painted the color of the bridge. This allowed the cameras to blend in with the surroundings.

Table 3: Camera Review and Performance During Pilot Surveys.

Camera	Recorded bats with built-in features?	Recoded bats with supplemental IR lights?	Settings Compatible with survey?	Scalable?	Evaluation
Moultrie Mobile Edge	No	No	Yes	No (expensive cloud storage)	Not recommended
Blaze Video	No	Yes, but low resolution	Yes	Yes	Not recommended
Reveal X-Pro 2	No	Yes, but low resolution	Yes	Yes	Not recommended
StealthCam	No	Yes, but low resolution	Yes	Yes	Not recommended
Reconyx Hyperfire 2	Yes	Yes	Yes	Yes	Recommended
Keen Reolink	Yes	Yes	Yes	Yes	Recommended

4.5 Create a New Predictive Model

The final classification based random forest model was built off of 1,500 trees, including 6 variables per tree split. Of the variables we examined, the most important in determining bat use included maximum bridge span lengths, bridge deck area and bridge length (Figure 4). The top two variables of importance are maximum bridge span lengths and deck area, both of which reveal a negative correlation with likelihood of bat presence (Figure 5). To evaluate model performance, we calculated the confusion matrix of the model and determined that the model performed well when determining which bridges are unlikely to have bats with a 0.12% error rate and performed poorly when determining which bridges are likely to have bats with an 88.5% error rate (Table 5). The model's poor performance at predicting bridges likely to have bats stems from the relatively small number of bridges known to be used by bats (46 from ESI and Lochmueller (2021) and 3 new bridges from the present study). This reflects a need for more data on bridges used by bats. In the absence of a larger dataset of used bridges, our model was able to generate a predicted probability of bat use for 11,998 bridges (26.5% of all bridges in the database), meaning that the bat use of most structures could not be predicted. Random forest uses the survey data as a training dataset to determine variables of importance, it then uses this model and predicts the likelihood of bat presence. While random forest was able to identify the most important variables, it cannot predict beyond the parameters of the training dataset.

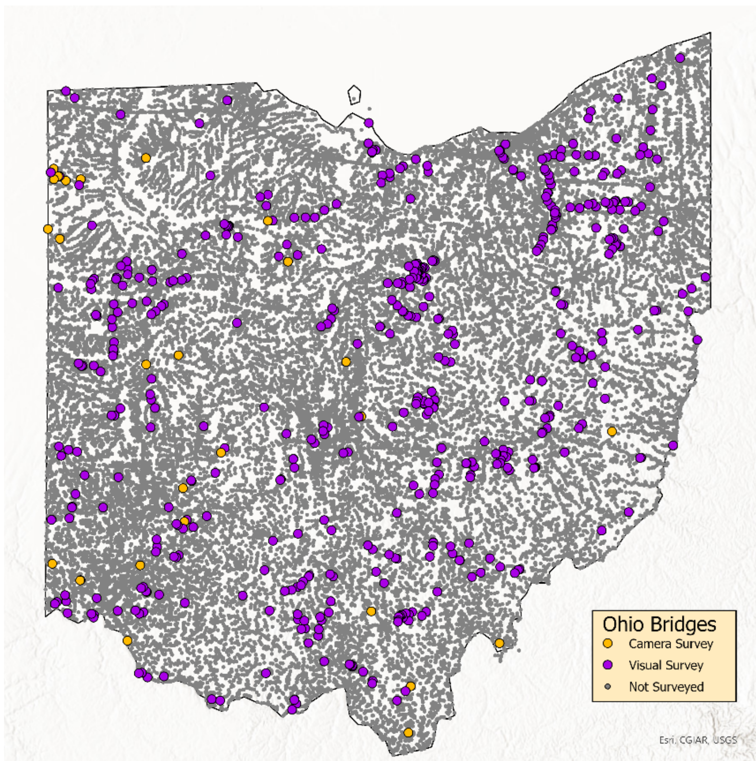


Figure 3: All 45,504 Ohio bridges present in March 2023; surveyed bridges are identified by survey method (camera or visual).

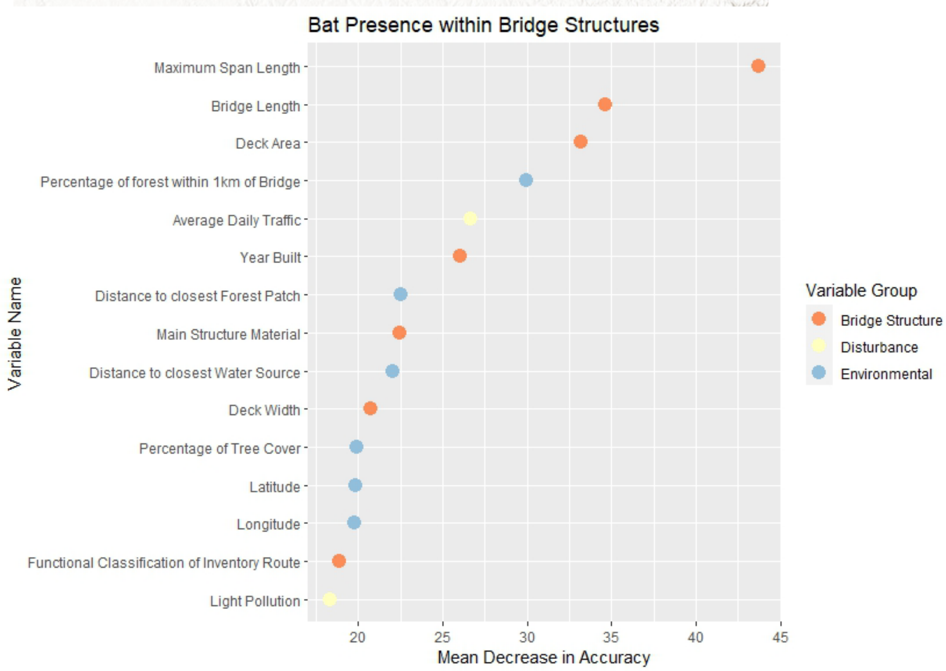


Figure 4: The 15 most important variables in the random forest analysis, listed from most (top of the Y-axis) to least (bottom) important when predicting bat presence within bridge structures.

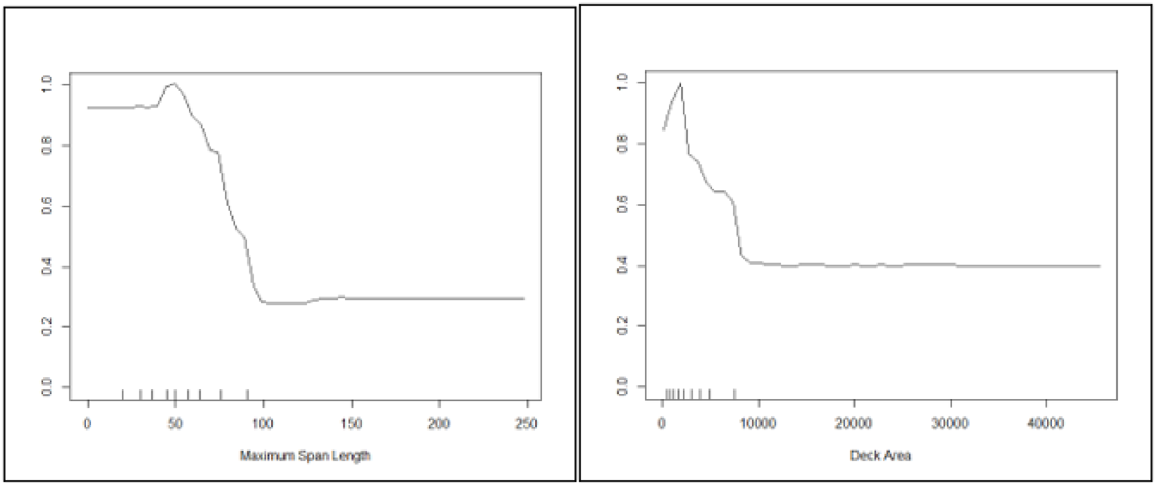


Figure 5: Partial dependency plots for the top two variables of the random forest model. Maximum span length and deck area were negatively correlated with likelihood of bat presence.

Table 5: Confusion matrix evaluating model performance; n=825 observations (504 from ESI and 321 from UC; nine UC observations have been removed due to inconsistencies with the data).

		Actual		
		No Bats	Yes Bats (False Positive)	Error Rate
Predicted	No Bats	772	1	0.12%
	Yes Bats (False Negative)	46	6	88.5%

4.6 Create a Virtual System to Interact with and Update Data

To improve upon the usability and longevity of ODOT's predictive model, we created BATMAP: a virtual cloud system allowing users to update survey data, visualize model results using a map-based interface, and view details of individual bridges as needed (Figure 6). BATMAP is a simple, streamlined tool that allows users to visualize data through the network in a user-friendly dashboard. This data is uploaded by users and provides a snapshot across time of bat behavior in the specific bridge. Each time data is updated, this will be added to the pool of data that exists, allowing existing bridge's data to be modified and updated, but also allows the addition of new bridges overtime, and the retention of data regarding bridges that are closed or no longer exist. Another key feature is that the results from the random forest analysis are included to show the likelihood of bats being present in a location. This information is found under the *All Bat Species Occurrence Ranking* data field. The rankings, *Low*, *Moderate*, and *High*, were derived from our model's probability that each bridge would be used by bats. Bridges with the Low ranking had occurrence probabilities between 0.0 and 0.49. Those with moderate ranks had probabilities between 0.50 and 0.74, and those with high had probabilities between 0.75 and 1. The remaining bridges are classified as Unknown. Bridges with confirmed bat presence are noted as *Surveyed - bats present,* and those with surveys finding no bats are noted as *Surveyed*

– *no bats seen*. Appendix 3 contains all information needed to access BATMAP, its System User Admin Features, and a description of all the fields in its database.

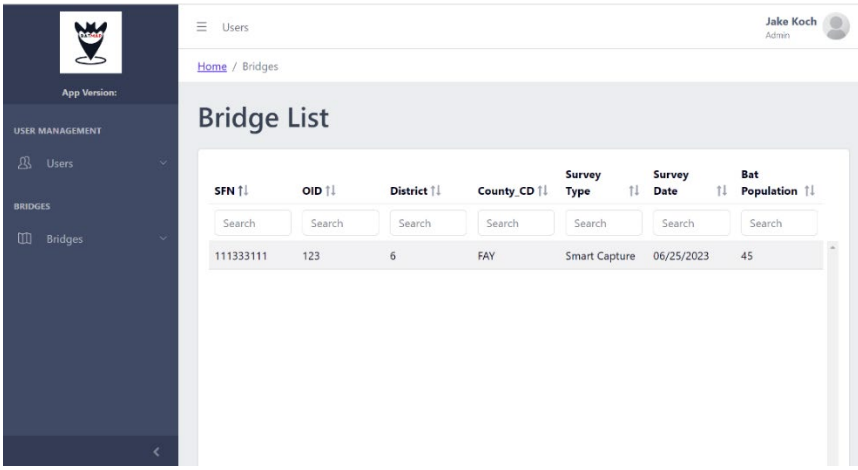


Figure 6: BATMAP Dashboard Landing Page

5.0 Recommendations for Implementation

We developed a method for camera-based passive surveys for bat use of bridges, identifying suitable technology for detecting bats and storing data in a useable format. This method, coupled with previous data from traditional visual surveys and a machine learning algorithm, allowed us to predict probabilities of bat presence in bridges throughout Ohio. We created a virtual system to store these data and visualize the results. Developed for a user-friendly experience and requiring minimal technical skills, BATMAP allows for easy queries of existing data and adding data over time.

Our review of ODOT's existing model (ESI and Lochmueller 2021) revealed several shortcomings in the analytical approach. We anticipated that a random forest approach to analyzing the data used in that model would produce more accurate insights into bat presence in bridges. While the model performance indicates this is true, the model could not predict bat use for most bridges in Ohio, demonstrating our own limitations. This is because we took a broad approach, attempting to assess a large number of potential explanatory variables. While this large set of predictor variables was intended to capture the diversity in the dataset (meaning the presence of bridges with highly variable physical characteristics found in diverse environmental settings) it was too complex for our dataset. That is, bridges throughout Ohio have a larger combination of structural and landscape features than our dataset composed of surveys from ESI and Lochmueller (2021) and our own surveys. When viewed in context, the 539 bridges with surveys that are contained BATMAP's database are a small fraction (1.2%) of all bridges in Ohio. Thus, our first recommendation is to simplify the models (reduce the complexity by decreasing the number of variables) for the short-term benefit of generating more insights from existing data. Second, we recommend that ODOT expand the database of bridge surveys for a more comprehensive understanding this complex problem in the long-term. This can be accomplished by funding professional surveys and asking local bridge inspectors to report observations into BATMAP. While local inspectors should not be expected to thoroughly survey bridges, when bats are present, these observations are tremendously useful as bridges occupied by bats represent the minority of ODOT's dataset (49 bridges), resulting in lower model confidence in predicting use versus absent. As a result, our second recommendation is that ODOT only place confidence into the results for bridges with a ranking of **low** in the *All Bat Species Occurrence Ranking* in BATMAP. However, we emphasize that many bridges are likely used by bats in Ohio, as 10% of surveyed bridges (52 of 539 bridges) in our database were used by bats.

Thus, we recommend that ODOT view the current implementation of their model for understanding bat use of bridges as an important step forward, but to embrace that much more data are needed. Our experience with camera-based surveys leads us to believe these tools, if used judiciously, can help to collect data efficiently in some settings. Judicious use of cameras means that only models with sufficient trigger speeds are used, and that additional IR illumination is provided. Cameras should only be placed such that suitable roosting habitat is in the field of view, and if necessary, that more than camera be used. Multiple cameras and additional lighting represent increased costs and logistical constraints. Over the long term, this method can provide a means to collect longitudinal data, opening the door to more robust analyses and conclusions. This must include sites that lack reliable cellular service, which was a limitation in our study design. However, we experienced logistical hurdles with these passive surveys, including theft and difficulties in capturing a large environment (an entire bridge) with a single camera. Thus, camera-based surveys remain a tool for consideration in certain contexts, but are far from replacing human surveys.

Finally, we recommend that ODOT maintain the database in BATMAP and annually update the random forest model. The process for updating BATMAP's database is described in Appendix 3, and instructions for running the random forest model were submitted as supplemental information.

6.0 WORKS CITED

[1] Adam, M. D., & Hayes, J. P. (2000). Use of bridges as night roosts by bats in the Oregon Coast Range. Journal of Mammalogy, 81(2), 402-407.

[2] Barré, K., Spoelstra, K., Bas, Y., Challéat, S., Kiri Ing, R., Azam, C., ... & Le Viol, I. (2021). Artificial light may change flight patterns of bats near bridges along urban waterways. Animal Conservation, 24(2), 259-267.

[3] Bektas, B. A., Hans, Z., Phares, B., Nketah, E., Carey, J., Solberg, M. K., & McPeek, K. (2018). Most likely bridges as roosting habitat for bats: study for Iowa. Transportation Research Record, 2672(24), 1-10.

[4] Carlos-Júnior, L. A., Creed, J. C., Marrs, R., Lewis, R. J., Moulton, T. P., Feijó-Lima, R., & Spencer, M. (2020). Generalized Linear Models outperform commonly used canonical analysis in estimating spatial structure of presence/absence data. PeerJ, 8, e9777. https://doi.org/10.7717/peerj.9777

[5] Civjan, S. A., Berthaume, A., Bennett, A., & Dumont, E. (2017). Bat Roosting in Bridges: Pros and Cons of Assessment Methods from a New England Regional Study. Transportation Research Record, 2628(1), 120-128. https://doi.org/10.3141/2628-13

[6] Dewitz, J. (2021). National Land Cover Database (NLCD) 2019 Products [Data set]. U.S. Geological Survey. https://doi.org/10.5066/P9KZCM54

[7] [ESI and Lochmueller 2021]. Environmental Solutions and Innovations Inc. and Lochmueller Group Inc. Seasonal use of Ohio Department of Transportation bridges by bats. 2021. https://rosap.ntl.bts.gov/view/dot/59870.

[8] Feldhamer, G. A., Carter, T. C., Morzillo, A. T., & Nicholson, E. H. (2003). Use of bridges as day roosts by bats in southern Illinois. Transactions of the Illinois State Academy of Science, 96(2), 107-112.

[9] Gore, J. A. and K. R. Studenroth Jr. 2005. Status and Management of Bats Roosting in Bridges in Florida. Florida Department of Transportation, Tallahassee, FL. Retrieved from [https://fdotwww.blob.core.windows.net/sitefinity/docs/default-source/research/reports/fdot-bd433-rpt94f4f153e1af4df39256a1da75af6d10.pdf?sfvrsn=d45bbcb0_2]

[10] Guillera-Arroita, G., Lahoz-Monfort, J. J., Elith, J., Gordon, A., Kujala, H., Lentini, P. E., McCarthy, M. A., Tingley, R., & Wintle, B. A. (2015). Is my species

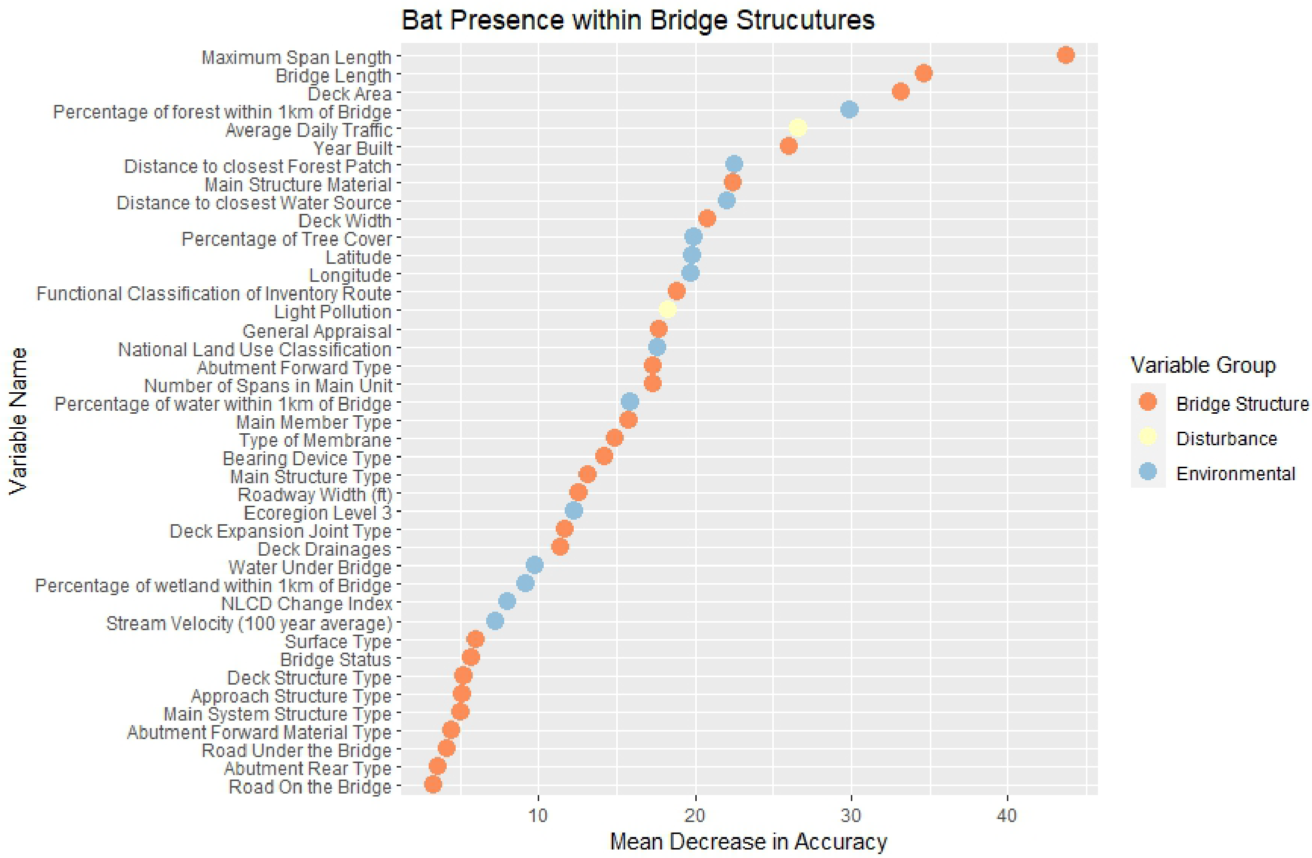
distribution model fit for purpose? Matching data and models to applications. *Global Ecology and Biogeography*, *24*(3), 276-292. https://doi.org/10.1111/geb.12268
[11] H. He and E. A. Garcia, "Learning from Imbalanced Data," in IEEE Transactions on Knowledge and Data Engineering, vol. 21, no. 9, pp. 1263-1284, Sept. 2009, doi: 10.1109/TKDE.2008.239.
[12] Hendricks, P., Lenard, S., Currier, C., & Johnson, J. (2005). Bat use of highway bridges in south-central Montana. Report to Montana Department of Transportation. Montana Natural Heritage Program, Helena. 31 pp.
[13] Jackson, J. G. and Cleveland, A. G. (2007). *Status and Management of Bats in Georgia Bridges*. (Contract with Department of Transportation, State of Georgia). In cooperation with U.S. Department of Transportation, Federal Highway Administration.
[14] Keeley, B., & Tuttle, M. (1999). Bats in American Bridges: Resource Publication No. 4 (No. RESOURCE PUBLICATION NO. 4). Bat Conservation International, Inc.
[15] Lance, R. F., Hardcastle, B. T., Talley, A., & Leberg, P. L. (2001). Day-Roost Selection by Rafinesque's Big-Eared Bats (Corynorhinus Rafinesquii) in Louisiana Forests. Journal of Mammalogy, 82(1), 166–172. https://doi.org/10.1644/1545-1542(2001)082<0166:DRSBRS>2.0.CO;2
[16] O'Shea, T. J., Bogan, M. A., & Ellison, L. E. (2003). Monitoring trends in bat populations of the United States and territories: status of the science and recommendations for the future. USGS Staff--Published Research, 35.
[17] Phares, B., Aldemir Bektas, B., Hans, Z., & Nketah, E. (2018). Assessing Bridge Characteristics for Use and Importance as Roosting Habitats for Bats: Final Report. Ames, IA: Bridge Engineering Center, Institute for Transportation, Iowa State University. Retrieved from [https://intrans.iastate.edu/app/uploads/2018/12/bridges_as_roosting_habitats_for_bats_w_cvr.pdf]
[18] RStudio Team (2020). RStudio: Integrated Development for R. RStudio, PBC, Boston, MA URL http://www.rstudio.com/.
[19] Russo, D., & Voigt, C. C. (2016). The use of automated identification of bat echolocation calls in acoustic monitoring: A cautionary note for a sound analysis. Ecological Indicators, 66, 598-602.

[20] [TIMS 2021] Transportation Information Mapping System. 2021. Ohio Department of Transportation. Accessed March 2023. < https://www.transportation.ohio.gov/working/data-tools/resources/03-tims>.

Appendix 1. Complete list of predictor (independent) variables used in the random forest model predicting which bridges would be used as day roosts by bats. Variables are placed into conceptual categories (see text) and labeled as categorical versus numeric data.

Category	Variable	Type	Source
Environmental	Change in Land Use	Categorical	USGS
	Distance to any water body	Numeric	USGS
	Terrestrial Ecoregion (Level 3)	Categorical	USGS
	Percentage of Tree Canopy Coverage	Numeric	USGS
	Land Use Classification	Categorical	USGS
	Percent of water within 1km radius	Numeric	USGS
	Distance to closest forest	Numeric	USGS
	Percent of forest within 1km radius	Numeric	USGS
	Latitude	Numeric	TIMS
	Longitude	Numeric	TIMS
	Water Under Bridge	Categorical	TIMS
	Stream Velocity	Numeric	TIMS
	Percent of wetland within 1km radius	Numeric	USGS
Disturbance	Average Daily Traffic	Numeric	TIMS
	Light Pollution	Numeric	NASA
Structural	Bridge Main Structural Material	Categorical	TIMS
	Bridge Main Structural Type	Categorical	TIMS
	Deck Area	Numeric	TIMS
	Number of Spans in Main Unit	Numeric	TIMS
	Bridge Status	Categorical	TIMS
	Abutment Forward Material Type	Categorical	TIMS
	Road Under the Bridge	Categorical	TIMS
	Road On the Bridge	Categorical	TIMS
	Surface Type	Categorical	TIMS
	Deck Expansion Joint Type	Categorical	TIMS
	Deck Drainages	Categorical	TIMS
	Bearing Device Type	Categorical	TIMS
	Type of Membrane	Categorical	TIMS

	Abutment Forward Type	Categorical	TIMS
	Main Member Type	Categorical	TIMS
	Maximum Span Length	Numeric	TIMS
	Bridge Length	Numeric	TIMS
	Approach Structure Type	Categorical	TIMS
	Deck Width	Numeric	TIMS
	Deck Structure Type	Categorical	TIMS
	Roadway Width	Numeric	TIMS
	Abutment Rear Type	Categorical	TIMS
	Functional Classification of Inventory Route	Numeric	TIMS
	General Appraisal	Numeric	TIMS
	Year Built	Categorical	TIMS

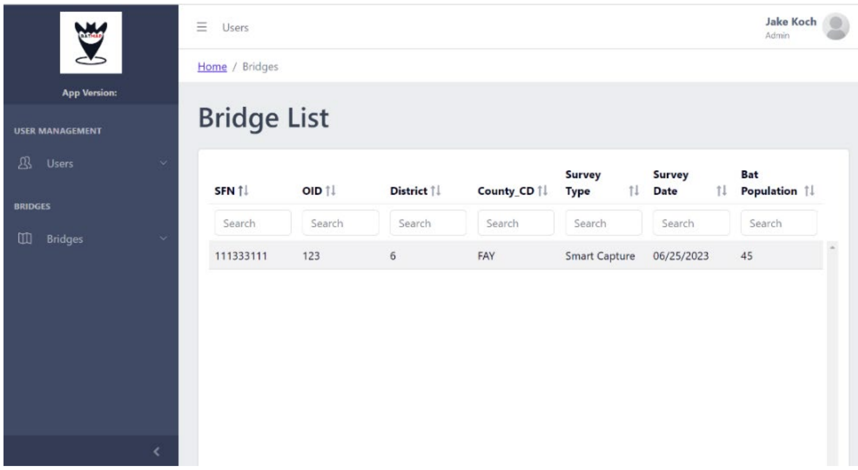


Bat Presence within Bridge Strucutures
Maximum Span Length
Bridge Length
Deck Area
Percentage of forest within 1km of Bridge
Average Daily Traffic
Year Built
Distance to closest Forest Patch
Main Structure Material
Distance to closest Water Source
Deck Width
Percentage of Tree Cover
Latitude
Longitude
Functional Classification of Inventory Route
Light Pollution
General Appraisal
National Land Use Classification
Abutment Forward Type
Number of Spans in Main Unit
Percentage of water within 1km of Bridge
Main Member Type
Type of Membrane
Bearing Device Type
Main Structure Type
Roadway Width (ft)
Ecoregion Level 3
Deck Expansion Joint Type
Deck Drainages
Water Under Bridge
Percentage of wetland within 1km of Bridge
NLCD Change Index
Stream Velocity (100 year average)
Surface Type
Bridge Status
Deck Structure Type
Approach Structure Type
Main System Structure Type
Abutment Forward Material Type
Road Under the Bridge
Abutment Rear Type
Road On the Bridge
Variable Name
10
20
30
40
Mean Decrease in Accuracy
Variable Group
Bridge Structure
Disturbance
Environmental

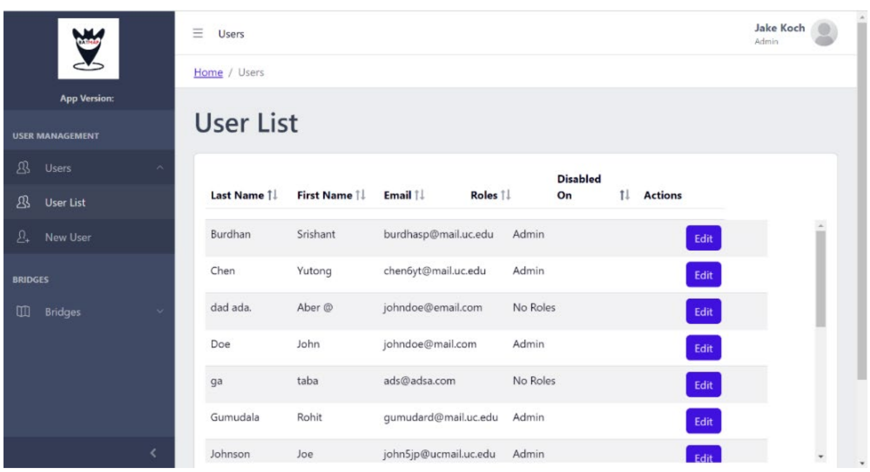
Appendix 3. BATMAP Features and Guide

System User Admin Features

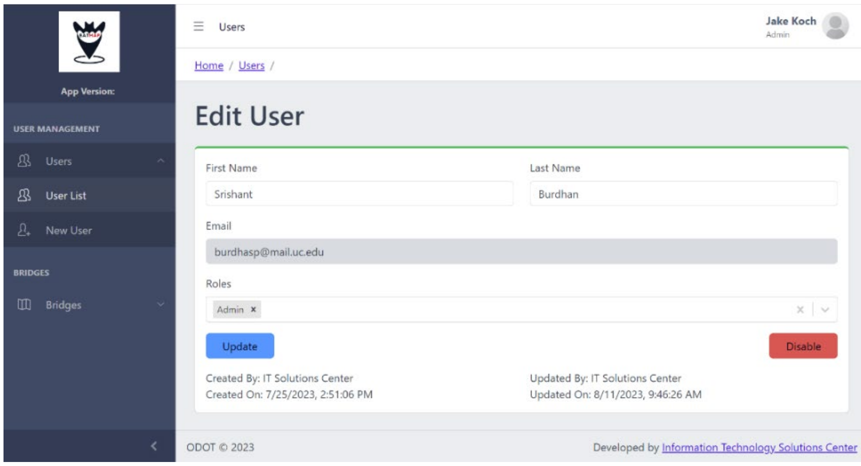
The image below shows the initial landing page that users will see when they first connect to BATMAP. The user will be greeted by a current list of bridges, along with a search bar to query the existing data. In the next sections, we outline the functionalities of the system and how each feature operates.



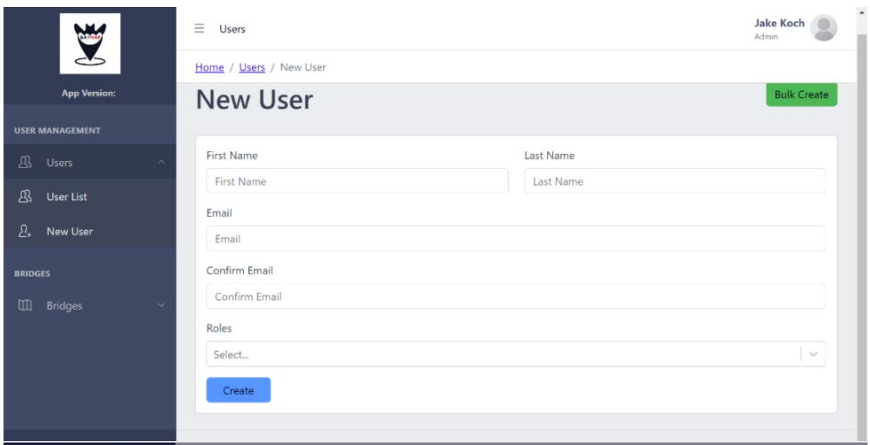
When clicking onto the "Users" tab on the left-hand menu, you see two different options that you can select. The first option is the "Users List" (below). This list shows the first and last name of all registered users, their e-mail address, and the roles that they are assigned. The last two columns denote whether the account is disabled, which is important for the security administrator of this system, and then the edit feature which allows you to modify the different aspects of users.



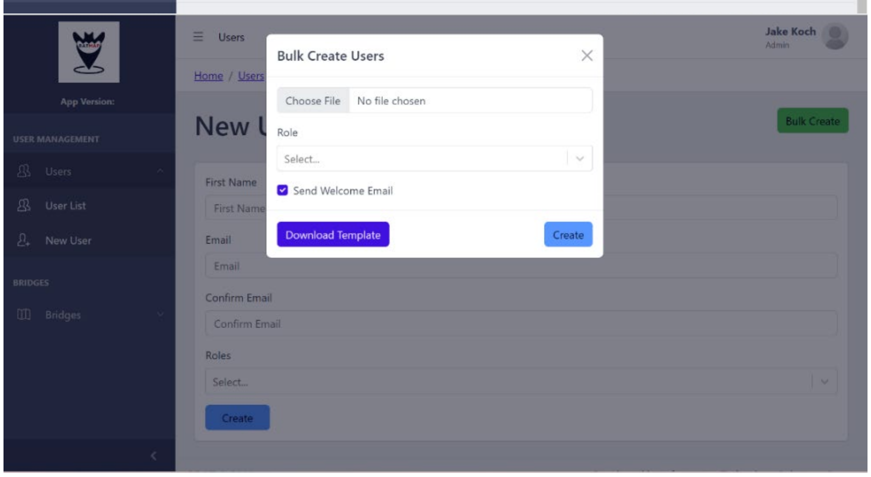
By clicking the "Edit" button in the image above, you can edit any of the attributes you have provided a user, after which you can click the update button or the disabled button based on your needs (below).



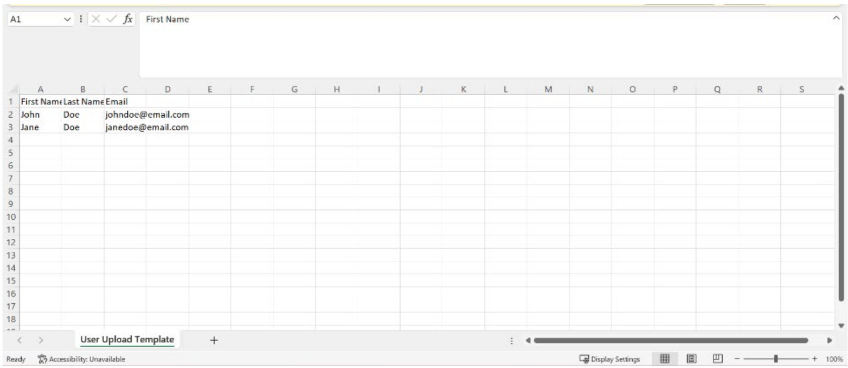
By allowing administrators to quickly edit users, ODOT can guarantee that records are up to date as they need to be changed. Adding a user is also easy and can be accomplished using the "New user tab" on the left-hand menu of BATMAP. This will provide you with the screen below.



Where you are able to create a user by entering the appropriate information and assigning a role. If you have many users to create you can use the bulk create feature (below).

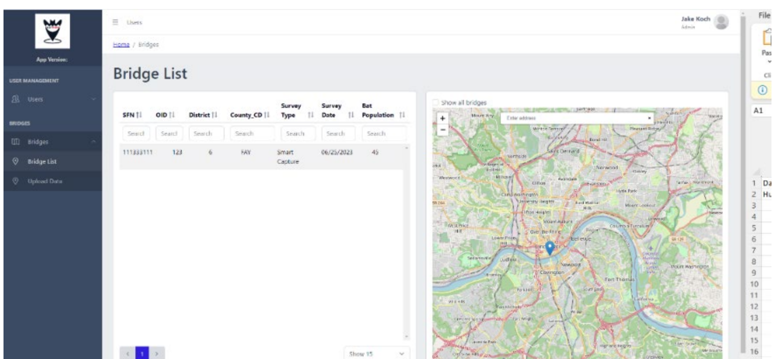


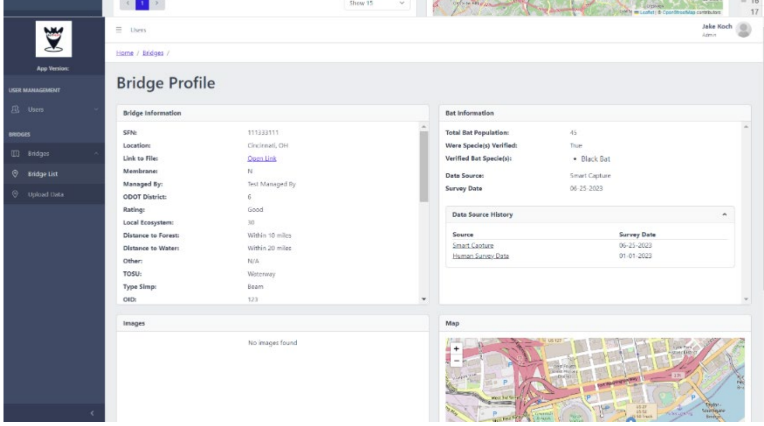
The bulk user creation features allows administrators to forgo the tedium of having to create many users individually. By using the provided template, an administrator can create users that are formatted properly which is seen in the image below. When creating users using this template, you are also able to send a welcome e-mail to users. This helps to ensure that users correctly created their accounts and receive a verification e-mail stating so. One thing to note however when creating users using the bulk creation option, all users will have the same role upon creation depending on your selection. This means that it may be helpful to divide users between administrative users and regular users.



Bridge List Repository Dashboard and Record Viewer

When clicking onto the "Bridge tab" on the left-hand menu of BATMAP there are two options, "Bridge List" and "Upload Data". By default, when you sign-on to BATMAP, you are brought to the "Bridge List" page. You can also arrive at this location by clicking the "Bridge List" option. Under the "Bridge List" option, users will find a list of all data that has been entered into BATMAP. This data will include things such as the SFN of the bridge, the type of survey done, the survey date, as well as other features of interest that researchers enter when using our bat sighting form and upload data portal. This information will also be accompanied by a pinpoint on the map which is seen in the image below, allowing for a clickable interface when trying to interact with data. Upon clicking or searching a record, the user will be taken to the "Bridge Profile" page, also below.

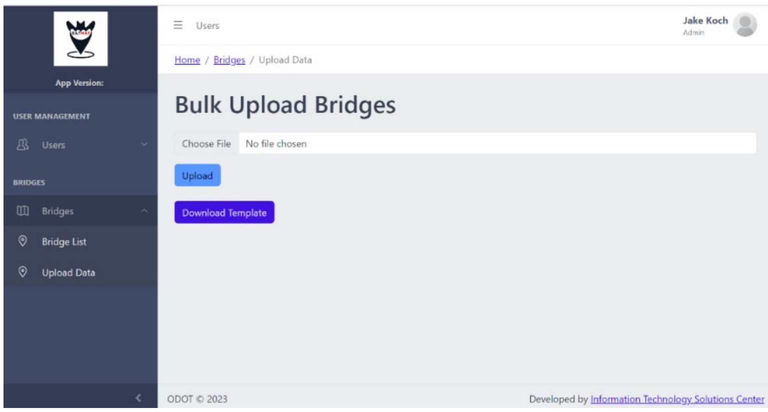




While in the Bridge Profile viewer you will be presented with data detailing all the information about the bridge, surveys throughout time, bat information such as populations and species, an image if applicable, a link to the videos if a video-based survey was done, and a pinpoint on a map of the location.

Managing Data in BATMAP

Uploading data to BATMAP can be accomplished easily using the upload data page under bridges. Users can download a template to format data so that it meets the required schema to be entered into BATMAP. By clicking the “Choose File” option, users can select files that they have already formatted. After selecting the appropriate file users can click “Upload” to update information in BATMAP. Users can download the template by clicking the download template button in the image below. Upon downloading the template, users will see the required fields that must be in the uploaded file, which must be a comma separated values (.csv) file.



To simplify workflow, we suggest uploading data to BATMAP once a year. This will reduce the chance of uploading duplicate entries. Importantly, BATMAP contains a column for “All Bat Species Occurrence Ranking”, which is based on the output of the random forest analysis. We recommend updating that analysis annually and updating the Occurrence Rankings prior to uploading new data.

Appendix 4. Random Forest Modeling Predictor Variables
Note: While some variables were retained from the TIMS system, others were modified to create meaningful categories that would better depict the influence of these variables on bat roosting suitability. In other cases, the categories were simply renamed for ease of computing, to keep all variables as numeric. Those fields that are different from their official designations are described below and marked with an asterisk (*). Highlighted fields represent the naming convention used in the final submitted datafile. All data gleaned from TIMS was downloaded March 2023.

LATITUDE_D Latitude; ODOT TIMS

LONGITUDE_D Longitude; ODOT TIMS

MAIN_STR_M NBI #043A Structure Type, Main: Kind of Material Main; ODOT TIMS
1 Concrete
2 Concrete continuous
3 Steel
4 Steel continuous
5 Prestressed concrete *
6 Prestressed concrete continuous *
7 Wood or timber
8 Masonry
9 Aluminum, Wrought Iron or Cast Iron
0 Other
99 Miscoded data
* Post-tensioned concrete coded as prestressed concrete

MAIN_STR_T NBI #043B Structure Type, Main: Kind of Material / Design, Main; ODOT TIMS
1 Slab
2 Stringer/Multi-beam or girder
3 Girder and floorbeam system
4 Tee beam
5 Box beam or girders - Multiple
6 Box Beam or girders - Single or Spread
7 Frame
8 Orthotropic
9 Truss - Deck
10 Truss - Thru
11 Arch - Deck
12 Arch - Thru
13 Suspension
14 Stayed girder
15 Movable - Lift
16 Movable - Bascule
17 Movable - Swing

18 Tunnel
19 Culvert
20 Mixed types
21 Segmental box girder
22 Channel beam
00 Other
99 Miscoded data

APPRH_STR_ NBI #044A Kind of Material, Approach; ODOT TIMS
1 Concrete
2 Concrete continuous
3 Steel
4 Steel continuous
5 Prestressed concrete *
6 Prestressed concrete continuous *
7 Wood or timber
8 Masonry
9 Aluminum, Wrought Iron or Cast Iron
0 Other
99 Miscoded data
* Post-tensioned concrete coded as prestressed concrete

MAIN_SPANS NBI #045: Number of Spans in Main Unit; ODOT TIMS
Number of spans in the main or major unit.

DECK_CD NBI #107: Deck Structure Type; ODOT TIMS
1 Concrete Cast-in-Place
2 Concrete Precast Panels
3 Open Grating
4 Closed Grating
5 Steel plate (includes orthotropic)
6 Corrugated Steel
7 Aluminum
8 Wood or Timber
9 Other
N Not applicable
99 Miscoded data

DECK_PROT_ NBI 108B: Type of Membrane; ODOT TIMS
1 Built-up
2 Preformed Fabric
3 Epoxy
8 Unknown
9 Other
0 None

N Not applicable (applies only to structures with no deck)
99 Miscoded data

YR_BUILT Year Built; ODOT TIMS

TYPE_SERV_ NBI #042A: Type of Service: On Bridge; ODOT TIMS
1 Highway
2- Railroad
3- Pedestrian/bicycle
4- Highway/railroad
5- Highway/pedestrian
6- Overpass, or second level of a multilevel interchange
7- Third level
8- Fourth level
9- Building or plaza
0- Other

TYPE_SERV1 NBI #042B: Type of Service: Under Bridge; ODOT TIMS
1 Highway
2 Railroad
3 Pedestrian/bicycle
4 Highway/railroad
5 Waterway
6 Highway/waterway
7 Railroad/waterway
8 Highway/waterway/railroad
9 Relief for waterway
0 Other

INVENT_RTE NBI #029: Average Daily Traffic (ADT); ODOT TIMS
Average daily traffic volume for the inventory route

GEN_APPRAI Ohio Item #67.01 General Appraisal; ODOT TIMS
The lowest of the Superstructure, Substructure or Supplemental Summary.

WW_ADEQUAC (*)- NBI #71 – Waterway Adequacy; ODOT TIMS

0 Bridge closed
2 Occasional or frequent overtopping of bridge deck and roadway approaches with severe traffic delays
3 Frequent overtopping of bridge deck and roadway approaches with significant traffic delays
4 Occasional overtopping of bridge deck and roadway approaches with significant traffic delays
5 Bridge deck above roadway approaches. Occasional overtopping of roadway approaches with significant traffic delays.

6 Bridge deck above roadway approaches. Occasional overtopping of roadway approaches with significant traffic delays.
11 Slight chance of overtopping bridge deck and roadway approaches. & Bridge deck above roadway approaches. Slight chance of overtopping roadway approaches.
9 Bridge deck and roadway approaches above flood water elevations (high water). Chance of overtopping is remote.
10 Bridge is not over a waterway.

MAX_SPAN_L NBI #048: Length of Maximum Span; ODOT TIMS
Length of the maximum (longest) span.

DECK_WD NBI #052: Deck Width, Out-To-Out; ODOT TIMS
The out-to-out structure width.

NBIS_BRIDG Ohio Item #306, NBIS Bridge Length; ODOT TIMS
Measurement along the centerline of the roadway between under copings of abutments or spring lines of arches, or extreme ends of openings for multiple boxes.

DECK_AREA Ohio Item #424 Deck Area; ODOT TIMS
The Deck Area is a product of the Bridge Deck Width (NBI #52) and Structure Length (NBI #49). In case of culverts, the deck area is product of the Approach Roadway width (NBI #32).

DECK_DRN_C (*) - Ohio Item #409 Deck Drainage Type; ODOT TIMS
1 Over the side (without drip strip)
2 Opening thru curbs or wheel guards
3 Scuppers and downspouts
4 Inlets with drain pipes
5 Drainage trough under open joints
6 Over the side
N None
0 Other (Natural off the bridge ends)

EXPN_JOINT (*) - Ohio Item #414A- Expansion Joint Type; ODOT TIMS
1 Metal Finger
2 Sliding Metal Plate Angle
3 Compression Seal
4 Poured
5 Open (Armored)
6 Open (Unarmored)
7 Steel Reinforced Elastomeric
8 Elastomeric Strip Seal
12 None
0 Other
10 Modular
11 Polymer modified expansion device

BEARING_DE (*) - Ohio Item #453- Bearing Device 1, Type; ODOT TIMS
1 Rollers
2 Rockers & Bolsters
3 Sliding, Bronze.
4 Elastomeric, Plain
5 Pot
6 Spherical
7 Disc
8 Fixed Arch-Rib
10 None
0 Other
11 Sliding, Other
12 Fixed
13 Elastomeric, laminated
14 Integral & semi-integral abutment bearings

LONG_MEMB_ (*) Ohio Item #474-Main Structure System; ODOT TIMS
10 two or more girder
11 two or more trusses, welded and riveted
12 two or more steel arches, welded and riveted
13 One or more concrete arches
14 Jack Arch
15 Not applicable (i.e. culvert, beam, slab, etc.)

MAIN_MEM_C (*) Ohio Item #475- Main Member Type; TIMS
1 Rolled steel
2 Riveted built-up steel
3 Welded built-up steel
4 Concrete tee beam
5 Concrete girder
6 Prestressed concrete box beam
7 Prestressed concrete I beam
8 Timber
9 Segmented Box Girder
0 Other (Concrete Rigid Frame)
10 Channel Beam
11 Cast-In-Place Concrete Box Beam
12 Slab
13 Not Applicable (Culverts, Trusses, Arches, etc.)

ABUT_FWD_T (*) Ohio Item #528- Abutment Forward- Foundation Type; TIMS

1 Gravity
2 Cantilever
3 Solid Wall
4 Cellular or “U” 5 Stub Gravity

6 Stub-Capped Pile (Single Row Piles)
7 Integral
8 Pedestal
9 Stub-Capped Pile (Multiple Row Piles)
0 Other
10 None
11 Proprietary Wall w/Stub Type Abutments
12 Capped Pile Bent
13 Cap & Column
14 Semi-Integral

ABUT_FWD_M (*) Ohio Item #527- Abutment Forward Material Type; TIMS
1 Stone
2 Concrete
3 Concrete and Stone
4 Timber
5 Steel
6 Steel and Timber
7 Steel and Concrete
11 None
0 Other

ABUT_REAR_ (*) Ohio Item #531- Abutment Rear Type; TIMS
1 Gravity
2 Cantilever
3 Solid Wall
4 Cellular or “U” 5 Stub Gravity
6 Stub-Capped Pile (Single Row Piles)
7 Integral
8 Pedestal
9 Stub-Capped Pile (Multiple Row Piles)
0 Other
10 None
11 Proprietary Wall w/Stub Type Abutments
12 Capped Pile Bent
13 Cap & Column
14 Semi-Integral

STREAM_VEL Ohio Item #663- Stream Velocity; ODOT TIMS
The hundred-year velocity of the stream under the bridge.

DEFIC_FUNC Bridge Status; ODOT TIMS

FUNCTIONAL NBI #026 Functional Classification of Inventory Roads; ODOT TIMS
RURAL
1 Principal Arterial (P.A.) Interstate

2 P.A. Other
6 Minor Arterial
7 Major Collector
8 Minor Collector
09 Local
URBAN:
11 P.A. Interstate
12 P.A. Freeway
14 P.A. Other
17 Collector
19 Local

ROADWAY_WI Roadway Width; ODOT TIMS
Total pavement width of a road segment

nlcd NLCD 2021 Land Cover Classifications; U.S. Geological Survey; (index value for each bridge location)
11 Open Water
12 Perennial Ice/Snow
21 Developed, Open Space
22 Developed, Low Intensity
23 Developed, Medium Intensity
24 Developed, High Intensity
31 Barren Lans (Rock/Sand/Clay)
41 Deciduous Forest
42 Evergreen Forest
43 Mixed Forest
52 Shrub/Scrub
71 Grassland/Herbaceous
81 Pasture/Hay
82 Cultivated Crops
90 Woody Wetlands
95 Emergent Herbaceous Wetlands

TreeCover Tree Canopy Cover. U.S. Forest Service. Version: 2021.4. (index value for each bridge location, measured as a percentage)

Light_Pollution Light Pollution. National Aeronautics and Space Administration. (index value for each bridge location, measured in SQM mag/arcsec^2)

Percent_Forest NLCD 2021 Land Cover Classifications; U.S. Geological Survey (percentage of area within 1 kilometer from bridge that is forest; wetland is classified by any pixels with the value of 41, 42, and 43)

Percent_Wetland NLCD 2021 Land Cover Classifications; U.S. Geological Survey
(percentage of area within 1 kilometer from bridge that is wetland; wetland is classified by any pixels with the value of 90 and 95)

Percent_Water NLCD 2021 Land Cover Classifications; U.S. Geological Survey
(percentage of area within 1 kilometer from bridge that is water; water is classified by any pixels with the value of 11)

DIST_FOREST NLCD 2021 Land Cover Classifications; U.S. Geological Survey
(shortest distance in kilometers from bridge to forest; water is classified by any pixels with the value of 41, 42, and 43)

DIST_WATER NLCD 2021 Land Cover Classifications; U.S. Geological Survey
(shortest distance in kilometers from bridge to water; water is classified by any pixels with the value of 11)

ECOREGIONS_L3 Ecoregions (Level 3)
55 Eastern Corn Belt Plains
57 Huron / Erie Lake Plains
61 Erie Drift Plain
70 Wester Allegheny Plateau
71 Interior Plateau
83 Eastern Great Lakes Lowlands

nlcd_change_index NLCD 2001-2021 Land Cover Change Index; U.S.Geological Survey; (index value for each bridge location)
1 no change
2 water change
3 urban change
4 wetland within class change
5 herbaceous wetland change
6 agriculture within class change
7 cultivated crop change
8 hay/pasture change
9 rangeland herbaceous and shrub change
10 barren change
11 forest change
12 woody wetland change
13 snow change