

1 Title: BatCount: A software program to count moving animals

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12 Abstract:

13 One of the biggest challenges with species conservation is collecting accurate and
14 efficient information on population sizes, especially from species that are difficult to count. Bats
15 worldwide are declining due to disease, habitat destruction, and climate change, and many
16 species lack reliable population information to guide management decisions. Current approaches
17 for estimating population sizes of bats in densely occupied colonies are time-intensive, may
18 negatively impact the population due to disturbance, and/or have low accuracy. Research-based
19 video tracking options are rarely used by conservation or management agencies for animal
20 counting due to the perceived training required to operate. In this paper, we present BatCount, a
21 free software program created in direct consultation with end-users designed to automatically
22 count aggregations of bats at cave roosts with a streamlined and user-friendly interface. We
23 report on the software package and provide performance metrics for different recording habitat

24 conditions. Our analysis demonstrates that BatCount is an efficient and reliable option for
25 counting bats in flight and has important implications for range- and species-wide population
26 monitoring. Furthermore, this software can be extended to count any organisms moving across a
27 camera including birds, mammals, fish or insects.

28

29 Introduction:

30 Effective species management and conservation hinges on accurate population
31 information. For species that are cryptic and/or difficult to count, such as bats, traditional
32 population estimates including visual, photographic counts, or mark/recapture techniques are
33 prone to bias (1). Furthermore, many methods to estimate populations require observers to enter
34 caves or roosts, disturbing threatened and endangered species during sensitive time periods that
35 may cause bats to abandon their roost, such as during the maternity season when adults care for
36 young. Additionally, entering caves can result in potentially exposing a colony to the pathogenic
37 fungus responsible for white-nose syndrome (2,3). Due to these limitations, populations of most
38 major bat caves are monitored less than would be desired to establish presence/absence at roosts,
39 calculate population trends over time, or gain additional life history information on the timing
40 and duration of seasonal migrations. As a result, we lack fundamental information on the
41 population of many bat species worldwide, especially species that are currently listed as
42 threatened or endangered. This lack of reliable population information for bats remains a priority
43 for many agencies including the U.S. Fish and Wildlife Service (4).

44 In the past several years, advances in technology have made thermal video systems more
45 user friendly and affordable, and many researchers and governmental agencies now use these
46 cameras to record animals in the darkness. Over a decade ago, the U.S. Army Corps of Engineers

47 created proprietary software (“T³”) integrated into a camera system to count bats from thermal
48 imagery (5), but the software has not been maintained and cannot be used with current thermal
49 imaging cameras. Recent advances in machine learning approaches and image analysis toolboxes
50 have resulted in several algorithms for tracking the movements of animals (6–11), yet these
51 products have not been widely used by users outside of academia, largely due to the perceived
52 training required to run the software (M. Armstrong, personal communication; V. Kuczynska,
53 personal communication; N. Sharp, personal communication). As a result, the few thermal
54 imagery population estimations conducted by biologists outside of academic institutions are
55 achieved with manual counts of video samples, which is a time-intensive process.

56 Motivated by the desire for a free, user friendly counting program that requires little
57 training and can be integrated with video formats from different camera manufacturers and
58 models, we developed BatCount software. This software was designed in collaboration with U.S.
59 Fish and Wildlife Service biologists, with a goal of quick adoption among management and
60 conservation agencies. Due to its intuitive graphical user interface, this software does not require
61 the user to have expertise in any coding languages, and as such is appropriate for broad use
62 among researchers, students, and even the general public. Furthermore, by paring down the
63 output results of the software and including a summary table and output video, we have
64 simplified the results to include the information most relevant to end users. Although created
65 with the main application of counting bats, due to the modifiable input parameters this software
66 can also be used to count birds, mammals, fish or insects.

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70 Materials and Methods

71 Availability and hardware requirements

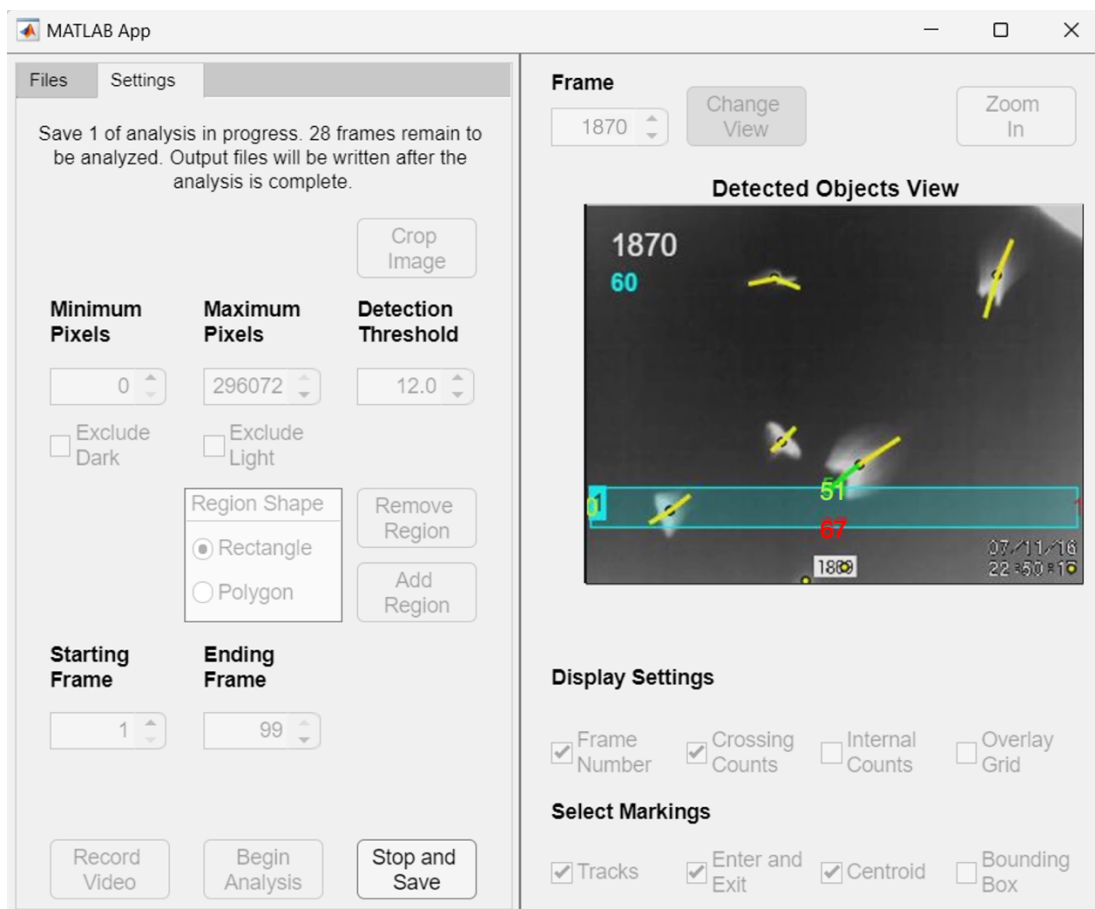
72 BatCount v1.24 was developed using MATLAB R2022a (MATHWORKS, Natick, MA)
73 and runs on Windows (Mac OS version in testing). The software uses a standalone interface that
74 does not require the user to purchase or install MATLAB. Rather, specific MATLAB routines
75 and toolboxes that are needed are automatically installed during the software installation.
76 Minimum hardware requirements to operate the software include 4 GB RAM and 2 GB video
77 card RAM, with 24 GB RAM and 4 GB video card RAM recommended for optimal
78 performance. Testing of the software was conducted with three different thermal cameras: 1) A
79 Viento 320 (Sierra-Olympic, Hood River, Oregon) with 320 x 240 resolution recording at 30
80 frames per second, 2) A FLIR Scion OTM 266 (Teledyne FLIR, Wilsonville, Oregon) with 640 x
81 480 resolution recording at 30 frames per second, and 3) a FLIR Photon (FLIR, Wilsonville,
82 Oregon) with 320 x 240 resolution recording at 30 frames per second. The software install file,
83 source code, and user guide can be downloaded at
84 <http://sites.saintmarys.edu/~ibentley/imageanalysis/pages/BatCount.html>.

85

86 *BatCount algorithm*

87 BatCount v1.24 first allows users to upload a video for analysis from its graphical user
88 interface. The program supports videos in multiple formats including .avi, .gif, .mj2, .mov, .mpg,
89 .mp4, and .wmv at any resolution and any frame rate. The program uploads videos and partitions
90 the videos into smaller video segments to improve performance as the video is analyzed. Its
91 interface then allows users to a preview any frame of the selected video, navigate between
92 frames, and edit the image for the preview (e.g., crop, zoom). The user can specify the frame

93 range in which to count bats, the maximum and minimum pixel range in which to consider an
94 object a bat, and the threshold, which determines the detection level in which the software will
95 detect an object against the background. The user can also specify one or multiple regions of
96 interest for tracking, which can be either a rectangle or a polygon with user specified vertices.
97 Additionally, users can choose to ignore all objects that are either lighter or darker than the
98 background. The final user-specified inputs include preview display settings (frame number,
99 crossing counts, internal counts, and overlay grid) and output video settings (tracks, enter and
100 exit, centroid, and bounding box). An example of the software interface is depicted in Figure 1.



101
102 **Figure 1: BatCount user interface with a video loaded and the detected object's view**
103 **toggled on.** This image was taken during an analysis of a video, so many of the adjustable user
104 parameters appear grayed out and not editable at this stage. A rectangular region of interest has

105 been specified on this frame to count the number of bats that pass through it. The bats' overall
106 flight trajectory starts from the top of the image and continues toward the bottom portion of the
107 screen, intersecting the rectangular region along their path. The frame number 1870 is shown in
108 white, and the crossing sum (60 in this case), which calculates the bats that move through the
109 rectangular region, is displayed below it. A net count of 51 bats have entered the top of the
110 region (shown in green), 67 have left the bottom of the region (shown in red), one net bat has
111 exited the right (shown in red) and no net bats have exited the left side (note the blue highlighted
112 1, which indicates the number of the selection box, slightly obscures the yellow 0 below). See S1
113 Video for the original video file used for this analysis, Table S1 for corresponding summary
114 output table and S2 Video for the software output video file. Note: for ease of visibility in the
115 manuscript we electronically manipulated the contrast of the box counting numbers due to partial
116 occlusion by the box and tracking line.

117

118 The software operates by detecting moving foreground objects (bats) against a
119 background. To account for motion relative to a static background, we use an adaptive process
120 for background determination by calculating the median value of the local segment of video
121 frames (as discussed in (12)). We also re-calculate the relationship between the background and
122 exiting bats over the video duration because the background color will continually change as a
123 result of dropping temperatures and resulting heat loss from the background surface at sunset.
124 The local segmented video frames are used so that the overall lighting is comparable between the
125 background and the frame of interest. The use of a median value as a background is based on the
126 reasoning that if bats are present at any given pixel for fewer than half of the frames, then the
127 median value will contain only background.

128 The tracking phase of the software results in a count of bats moving across the user
129 specified regions. The software determines connecting lines (“tracks”) relating the center of one
130 detected object across subsequent frames using a nearest neighbor approach. More specifically,
131 the tracks are calculated by comparing three sequential frames. First, the center of a bat is
132 determined in the current frame and the prior frame. Based on these positions the center is
133 predicted for where a bat should be on the future frame, assuming linear motion. If the predicted
134 location is within the bounding box for a bat in the future frame, then a line is drawn indicating a
135 correctly predicted future track. The same process is run backward to determine prior tracks. The
136 corresponding tracks for forward and backward tracks are used to determine if a bat has entered
137 or exited a user specified region of interest. These crossing counts are ultimately used to
138 determine overall counts for the videos.

139 Upon completion of the counting, the software outputs 4 files: 1) an output summary
140 table, 2) an output settings file, 3) a detailed counting log of the number of bats both in the entire
141 frame and in the region of interest, and 4) if specified by the user, an output video overlaid with
142 detected objects and tracks. An example of an output summary table is shown in Table 1 with the
143 corresponding explanation of the output results table illustrated in Figure 2. See supplemental
144 information for example test video (S1 Video) and corresponding output files (S1 Table and S2
145 Video).

146

147 Table 1: Example output summary table. See Eq. 1 and 2 for explanation of the crossing and
148 emergence sums. The values represented in parentheses are the actual values calculated for the

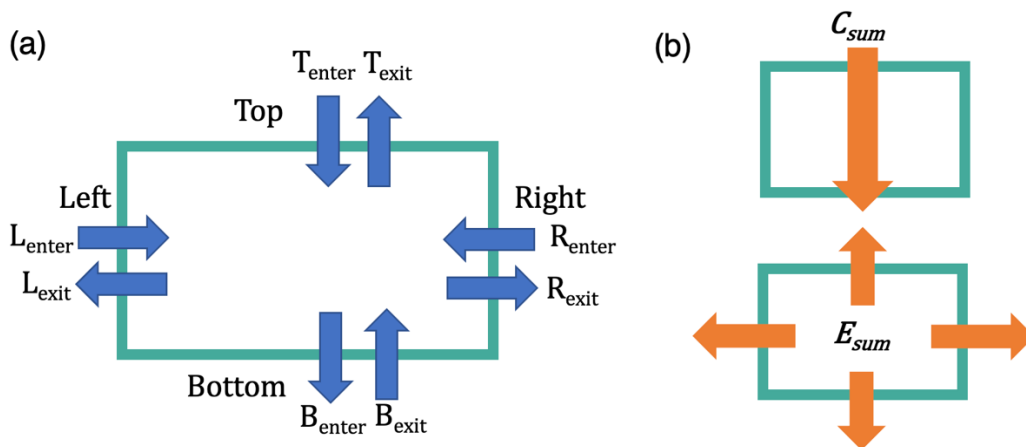
149 example shown in Figure 1 (see also S1 Video).

	Top	Right	Bottom	Left	Crossing and Emergence Sums
Enter	T_{enter} (88)	R_{enter} (0)	B_{enter} (33)	L_{enter} (0)	C_{sum} (60)
Exit	T_{exit} (37)	R_{exit} (1)	B_{exit} (100)	L_{exit} (0)	E_{sum} (17)

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154 Figure 2: Illustration of the output summary results table based on the user selected region. This
 155 example shows the output for a rectangular box. (a) The software counts the total number of bats
 156 entering and exiting each side of the selection box for the entire video. (b) illustration of the bat
 157 flight profiles that would be appropriate for using the Crossing sum, C_{sum} (Eq. 1), and
 158 Emergence sum, E_{sum} (Eq. 2). The C_{sum} should be used when counting bats transiting across the
 159 user selected region, whereas the E_{sum} should be used when counting bats emerging from a
 160 central position within selected region.

161

162

163 The software compiles the enter and exit values as bats cross each region of the rectangular box
164 or polygon, as well as calculates two summation metrics. The crossing summation metric, C_{sum} ,
165 sums the number of bats if bats are moving across the field of view of the camera in one
166 generally polarized direction, such as bats emerging from a cave opening. For a rectangular
167 region of interest this is calculated by summing the larger of the entering or exiting values on
168 each side:

$$170 \quad C_{sum} = \frac{1}{2} (|(T_{>} - T_{<}) + (B_{>} - B_{<}) + (L_{>} - L_{<}) + (R_{>} - R_{<})|) \quad \text{Eq. 1}$$

171
172 where T denotes the top side, B denotes the bottom, L denotes the left, and R denotes the right
173 (Figure 2). Here the greater than and less than correspond to the greater or and lesser, values of
174 the entering count and the exiting counts. This automatic determination of the largest value,
175 between enter and exit counts, allows for counting of bats crossing the camera's field of view in
176 any direction. In the crossing sum, the values are divided by 2 to account for the double
177 counting of the same bat entering a region of interest on one side and exiting on another, such as
178 a bat moving from left to right or top to bottom.

179 The emergence summation metric, E_{sum} , corresponds to the number of bats leaving or
180 entering a region of interest, such as if bats are emerging from a bat box, tree, pit cave, or if the
181 camera was pointed directly facing a cave opening. This is calculated by:

$$183 \quad E_{sum} = |(T_{enter} - T_{exit}) + (B_{enter} - B_{exit}) + (L_{enter} - L_{exit}) + (R_{enter} - R_{exit})| \quad \text{Eq. 2}$$

184
185 where the difference in respective number of bats entering and exiting each side is calculated.

186 For videos where there is bulk movement across the region of interest the C_{sum} metric is
187 greater and for videos where there is bulk movement into or out of a region of interest the E_{sum}
188 metric is larger. Both output counts are saved in the output data file and the larger of the two
189 values is displayed in the interface below the frame number. For example, Table 1 depicts the
190 actual counts in the summary output file for the example illustrated in Figure 1. The value listed
191 at the top of the selection box in Figure 1 $T_{enter} - T_{exit} = 51$, corresponds to 51 more bats
192 entering (green) the top than had exited. Similarly, the net value $R_{enter} - R_{exit} = -1$,
193 corresponds to one more bat exiting (red) the right than had entered. Similarly, $L_{enter} - L_{exit} =$
194 0 corresponds to no net bats traveling across the left portion, and $B_{enter} - B_{exit} = -67$,
195 corresponds to 67 more bats exiting the bottom than entering. Based on these count differences:
196 $C_{sum} = 59.5$, which has been rounded to 60 and is displayed below the frame number and
197 written in cyan to match the cyan color region of interest. $E_{sum} = 17$, and while displayed in the
198 summary output table is not visible on the software interface because it is the smaller of the two
199 numbers. If E_{sum} was greater than C_{sum} , its value instead would be displayed and shown in cyan.
200 See S1 Video for the original video file used for this analysis, Table S1 for corresponding
201 summary output table and S2 Video for the software output video file.

202 It is important to emphasize that the user should think carefully about the count values
203 most appropriate for their video. For example, C_{sum} was designed for videos in which bats are
204 truly crossing opposing regions of the selection box, i.e., top to bottom or left to right. For some
205 recording scenarios, bats may be entering crossing adjacent corners, such as entering from the
206 top and exiting the right. In these situations, relying on C_{sum} will substantially undercount the
207 bats, and it would instead be better to use the enter and exit counts from one region of the
208 selection box, such as the top. As such, users of the software should always preview the

209 emergence video to determine the summary table output value that is most appropriate given the
210 overall bat flight behavior.

211

212 *Software accuracy*

213 We evaluated the accuracy of the software with thermal recordings from 8 different
214 locations: 6 *Myotis grisecens* (MYGR, gray bats) and 2 *Tadarida brasiliensis* (TABR, Brazilian
215 free-tailed bat) maternity roosts. Date, location, software accuracy, and camera information for
216 each recording is listed in Table 2. We chose videos with different roost types, species,
217 background clutter, bat densities, and emergence profiles to represent the diversity of
218 applications by the end user. Due to the length of recordings and density of bats in the videos at
219 the maternity caves, manual counts of the entire video were prohibitive. Instead, we randomly
220 selected n replicates (see Table 1) of 900-frame video segments from each emergence recording
221 for manual counting. Counting was conducted by trained technicians unaware of software
222 program results. During the initial training period, the technicians both unknowingly counted the
223 same video segments and had manual counts within 96.5% of each other. After the training
224 period, technicians unknowingly overlapped 10% of their video segments so we could ensure
225 continued accuracy in counting. Manual counts were conducted with a frame-by-frame analysis
226 using the KMPlayer software (version 4.2.2.58) in 50 frame segments. To expedite counting, we
227 manually counted bats entering and exiting one of the four rectangular regions (the same region
228 and side for each video) and compared the performance of the software to the manual counts.

229

230 Table 2: Recording date (month/day/year), location (county, state), camera type, average number
231 of bats per 900-frame segment, number of video segments included in the analysis, and overall
232 software accuracy for each of the 8 recordings used to evaluate the software.

CaveID	Recording date	Location	Camera	Bats/seg	# video segments	Software accuracy
MYGR1	07/17/2020	Camden, MO	Viento	122	20	91.3%
MYGR2	06/25/2021	Taney, MO	FLIR scion	188	20	90.1%
MYGR3	06/25/2021	Wright, MO	FLIR scion	163	20	94.8%
MYGR4	06/22/2021	Oregon, MO	FLIR scion	252	11	72.0%
MYGR5	??/??/2012	Wilson, TN	FLIR photon	146	20	50.8%
MYGR6	08/13/2021	Nelson, KY	FLIR photon	24	20	56.7%
TABR1	06/13/2016	Woods, OK	Viento	771	20	83.6%
TABR2	06/15/2016	Woodward, OK	Viento	718	20	70.8%

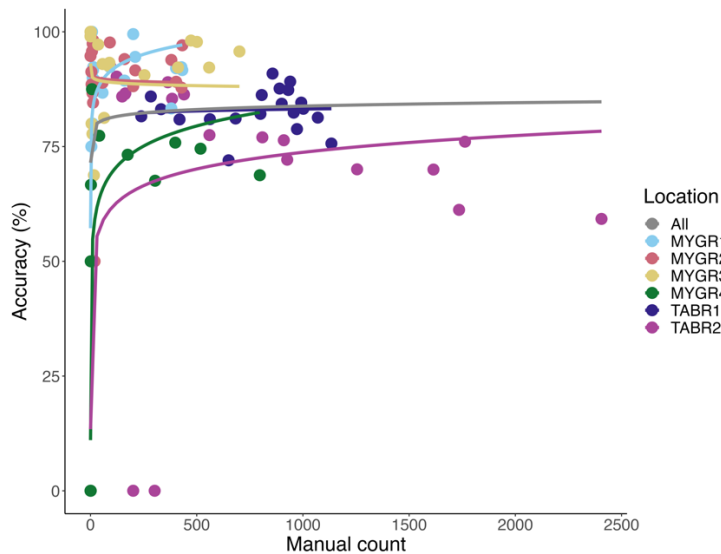
233

234 Results and Discussion

235 At the maternity roosts, BatCount software accuracy ranged from 94.8 to 50.8% (Table
236 2). Software performance strongly depended on video quality, with the highest performance
237 achieved for videos with strong contrast between the bats and the background and minimal
238 overlap of bats. Our peak accuracy of 94.8% is slightly higher than the reported accuracy of 93%
239 for the T3 system (5). Camera model also affected performance, with videos recorded by the
240 FLIR Scion and Viento cameras (average performance 85.6 and 81.9%, respectively)
241 outperforming those recorded by the FLIR photon camera (average performance 53.8%). The
242 poor accuracy of the videos MYGR5 and MYGR6 was due primarily to a combination of low
243 background contrast and poor video resolution; even our trained technicians struggled to visually
244 discriminate bats against the background. Therefore, we cannot disambiguate whether the poor

245 performance for these two locations is due to camera quality, environmental conditions, or both.
246 Due to these limitations, we removed MYGR5 and MYGR6 from further analysis.

247 Figure 3 illustrates the accuracy of the software as a function of the number of bats in
248 each 900-frame (30 second) segment for each cave location. At all locations, the software
249 underestimated bat counts. The data are best represented overall with a logarithmic fit, in which
250 accuracy is low at low numbers of bats but remains relatively stable for medium densities of
251 bats. When bats began to overlap at higher emergence densities (TABR1, TABR2), the chance of
252 the software counting two bats as one increased, and accuracy begins to decline. We are
253 currently developing a neural network approach to better count overlapping bats and expect an
254 increase in software accuracy with its incorporation. All updates of the software will be released
255 on the software website and announced via authors' social media.



256
257 Figure 3: Performance curves based on number of bats in each video segment. At low numbers
258 of bats (< 50 bats per 30 second segment), the software demonstrated variable accuracy. At
259 medium numbers of bats (between 50 and 800 bats per 30 second segment), the software
260 performance remained stable, with location affecting overall accuracy. At high numbers of bats
261 (> 800 per 30 second segment), performance began to decline as bats overlapped.

262

263 Although the exact processing time of the software depends on the length of the video
264 and number of bats in each recording, we can make some general statements about the software
265 processing time. Using the minimum hardware requirements listed to run the software, the
266 software processes approximately 1 frame per second. Computers with the recommended
267 specifications can process approximately 2 frames per second. For example, an emergence that
268 lasts 60 minutes and was recorded at 30 frames per second would take approximately 15 hours to
269 process. This time can be partitioned by counting specific segments of the longer emergence
270 video. We also found it helpful to run the counting software overnight. In comparison, our
271 trained technicians manually counted the more challenging videos at a rate of 1 frame every 2
272 minutes. Thus, with standard PC equipment our software can count bats 250 times faster than
273 human effort and reduces human bias. The speed of the software can be further accelerated by
274 using a supercomputer, which should be able to process an entire emergence video in less than a
275 second. The next step for this software is integration into the ground-truthing component of a
276 method to estimate animal populations with passive acoustics (13).

277 In conclusion, with our performance testing we know that the current version of our
278 software is highly accurate when recording gray bats with a high-resolution camera. Future
279 releases of the software will increase performance for dense bat flights. By developing the
280 software in close consultation with and testing from end-users, we have developed a counting
281 software that is intuitive, easy to use, and provides informative summary output including total
282 counts and an output video. This software eliminates the need to exhaust our most precious
283 resource as a conservation community—time. We are currently working with end-users to
284 develop and implement best practices for both placement of cameras in the field and placement

285 of the user-defined selection boxes for software counting. This software provides a free and
286 powerful tool to obtain population counts of bats emerging from roosts and can be a valuable
287 resource to aid in population estimation and species conservation.

288

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300

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