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8   RH: Cook et al. • Decision analysis guides disease risk assessments

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10   Evaluating the risk of SARS-CoV-2 transmission to bats using a decision analytical
11   framework

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27   **ABSTRACT** Preventing wildlife disease outbreaks is a priority issue for natural resource

28   agencies, and management decisions can be urgent, especially in epidemic circumstances. With

29   the emergence of SARS-CoV-2, wildlife agencies were concerned whether the activities they

30   authorize might increase the risk of viral transmission from humans to North American bats but

31   had a limited amount of time in which to make decisions. We provide a description of how

32   decision analysis provides a powerful framework to analyze and re-analyze complex natural

33   resource management problems as knowledge evolves. Coupled with expert judgment and

34   avenues for the rapid release of information, risk assessment can provide timely scientific

35   information for evolving decisions. In April 2020, the first rapid risk assessment was conducted

36   to evaluate the risk of transmission of SARS-CoV-2 from humans to North American bats.

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37   Based on the best available information, and relying heavily on formal expert judgment, the risk

38   assessment found a small possibility of transmission during summer work activities. Following

39   that assessment, additional knowledge and data emerged, such as bat viral challenge studies, that

40   further elucidated the risks of human-to-bat transmission and culminated in a second risk

41   assessment in the fall of 2020. We update the first SARS-CoV-2 risk assessment with new

42   estimates of little brown bat (*Myotis lucifugus*) susceptibility and new management alternatives,

43   using findings from the prior two risk assessments and other empirical studies. We highlight the

44   strengths of decision analysis and expert judgment not only to frame decisions and produce

45   useful science in a timely manner, but also to serve as a framework to reassess risk as

46   understanding improves. For SARS-CoV-2 risk, new knowledge led to an 88% decrease in the

47   median number of bats estimated to be infected per 1000 encountered when compared to earlier

48   results. The use of facemasks during, or a negative COVID-19 test prior to, bat encounters

49   further reduced those risks. Using a combination of decision analysis, expert judgment, rapid risk

50   assessment, and efficient modes of information distribution, we provide timely science support to

51   decision makers for summer bat work in North America.

52   **KEY WORDS**: bats, expert judgment, SARS-CoV-2, structured decision making, risk analysis,

53   zoonosis

54   The emergence of severe acute syndrome coronavirus 2 ("SARS-CoV-2") occurred in the fall of

55   2019 and quickly presented immediate and apparent health risks to humans worldwide. By

56   March 2021, the novel pathogen and associated coronavirus disease ("COVID-19") had resulted

57   in over 34 million documented human disease cases and over 800,000 deaths globally (Dong and

58   Du 2020; Johns Hopkins COVID-19 Dashboard). While the human health risks of COVID-19

59   are clear, empirical information on the risk to wildlife is less available, and thus there remains

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60 concern among North American natural resource managers for the potential that SARS-CoV-2

61 could be transmitted to wildlife from infected humans. Bats are a group of primary focus

62 following the detection of a closely related betacoronavirus in a horseshoe bat (*Rhinolophus*

63 *affinis*) in eastern Asia (Olival et al. 2020); however, empirical study to directly assess the threat

64 that SARS-CoV-2 presents to bats remains limited. Thus, there is an ongoing need for formal

65 risk assessments that can best integrate existing knowledge and guide pressing management

66 decisions regarding activities that require human-bat interaction.

67

68 When first confronted with the potential for SARS-CoV-2 exposure and infection in North

69 American bats, natural resource managers had a limited suite of options to reduce the associated

70 risk, including: proceeding as usual with minimal restrictions; placing a moratorium on all work

71 under their authority that may elevate risk; or adopting mitigation actions thought to reduce risks.

72 However, justification for selecting any one of these actions was a challenge because of the

73 many uncertainties that obscured identification of an optimal approach. A few of the most

74 pressing uncertainties surrounded bat species susceptibility, dominant transmission pathways,

75 and estimation of the relative exposure and transmission risk that different human-bat

76 interactions presented. Decisions had to be made without waiting for research that could reduce

77 these uncertainties. To help managers make urgent decisions with limited information and under

78 uncertainty, a series of rapid risk assessments were performed in 2020 using a decision-making

79 approach that helped to: (1) identify agency objectives; (2) guide the development of quantitative

80 models that were explicitly linked to agency objectives; (3) maximize the utility of available data

81 and knowledge; and, (4) assess management alternatives under dynamic and frequently changing

82 conditions.

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84   In April 2020, a first assessment was completed that estimated the risk of SARS-CoV-2

85   transmission to North American bats during summer activities. The assessment was guided by a

86   structured decision-making approach using an interagency team to evaluate the best course of

87   action for management agencies based on the identified objectives, uncertainties, and a risk

88   model that explicitly linked objectives and possible mitigation actions (Runge et al. 2020). The

89   focal species for that assessment was the little brown bat (*Myotis lucifugus*) and risks associated

90   with conducting research, survey, monitoring, and management (RSM), wildlife rehabilitation

91   (WR), and wildlife control (WC) activities during the North American spring and summer

92   seasons were assessed. The primary RSM activities of concern were those that put scientists in

93   close proximity to bats as part of efforts to study and mitigate the effects of white-nose syndrome

94   ("WNS"; e.g., Hoyt et al. 2019), a fungal disease that has caused declines of over 90% in

95   affected little brown bat populations (Cheng et al. 2021); activities from other workers included

96   removal and exclusion of bats from human dwellings (WC) and the care of injured bats (WR).

97   Much of the information used for the assessment was derived from a formal process of expert

98   judgment, as empirical data about the human and wildlife potential of SARS-CoV-2 were largely

99   unknown at the time.

100

101   The first assessment by Runge et al. (2020) estimated that the risk of SARS-CoV-2 transmission

102   from humans to bats was non-negligible and that the risk could be reduced if well-fitted N95

103   respirators (a type of mechanical filter capable of removing viral particles from exhaled breath of

104   infectious individuals) and other protective clothing were used during all human-bat interactions.

105   In the analysis, critical uncertainties remained–most notably a high level of uncertainty about the

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106   probability of bat susceptibility. The authors noted that the existence of a decision framework

107   complete with objectives, a quantitative risk model, and management alternatives (e.g.,

108   mandating use of N95 respirators, prohibiting certain permitted activities) could be used to

109   rapidly update decisions as more empirical information was gained.

110

111   In the fall of 2020, another assessment was conducted that evaluated the risk of human-to-bat

112   transmission of SARS-CoV-2 during winter research activities. Winter activities primarily occur

113   in enclosed spaces, such as hibernacula and winter roosts, that were thought to increase the

114   potential risk of exposure of the bats to aerosolized virus emitted by scientists (Cook et al. 2021).

115   Thus, included in that assessment were new data on the effectiveness of facemasks to reduce

116   viral emission of infectious humans, and new knowledge regarding the susceptibility of bat

117   species to SARS-CoV-2. Importantly, by the time of the second assessment, two bat challenge

118   studies had been conducted in laboratory settings; one found no viable infection in big brown

119   bats (*Epstesicus fuscus*), and another found that fruit bats (*Rousettus aegyptiacus*) were

120   somewhat susceptible (Hall et al. 2020, Schlottau et al. 2020). Additionally, studies on species-

121   specific angiotensin-converting enzyme 2("ACE2") sequences, an indicator of viral binding

122   potential, shed further light on potential bat susceptibility (e.g., Damas et al. 2020). In aggregate,

123   experts estimated a much lower, and less uncertain, probability of infection for several bat

124   species, including the little brown bat (Cook et al. 2021). New information about the importance

125   of aerosols for human disease transmission and the effectiveness of other personal protective

126   equipment (PPE) and COVID-19 testing for preventing exposure was incorporated into a risk

127   model for winter bat work.

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129   As we transition into another summer season (2021), the empirical data on bat susceptibility,

130   human viral shedding dynamics, and the potential effectiveness of facemasks and COVID-19

131   testing to reduce bat exposure have provided sufficient justification to revisit the initial decision

132   analysis and summer risk assessment. In this paper, our objective was to provide updated risk

133   estimates for summertime RSM, WC, and WR activities. We first confirm that the structural

134   elements of the decision framing from Runge et al. (2020) remain relevant to agencies

135   considering summer bat work. We then update probability of susceptibility estimates for the little

136   brown bat based on Cook et al. (2021) and re-evaluate the risk of SARS-CoV-2 human-to-bat

137   transmission during summertime RSM, WC, and WR activities. We evaluate the effectiveness of

138   COVID-19 testing, in addition to several new types of enhanced PPE, for their ability to prevent

139   exposure and mitigate risk. We highlight the strengths of decision analysis to organize, evaluate,

140   and improve time-sensitive decisions using expert knowledge, strategic decision framing, and

141   frequent updating. We also provide a brief synopsis of a few institutional hurdles that challenged

142   the delivery of our risk assessments to decision-makers and provide some potential options to

143   improve the speed of decision-relevant science in future studies.

144   **METHODS**

145   **Decision Framing and General Approach**

146   The initial decision framing for SARS-CoV-2 transmission risk from humans to bats formed the

147   basis for the results presented in Runge et al. (2020) and Cook et al. (2021). A diverse group of

148   state and federal decision makers were involved in the framing, and as a result, it captured many

149   of the objectives and management alternatives that agency decision makers were considering at

150   the time. The framing of a decision may change over time and can lead to different structuring of

151   the problem and resulting models. Therefore, to update the summer risk assessment we first

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152   revisited the original decision framing for spring and summer work with the original guidance

153   committee from Runge et al. (2020). During our meeting, agency participants indicated that the

154   decision context and all objectives remained the same. Of particular relevance to this assessment

155   were objectives related to:

156

157   (1) minimizing the morbidity and mortality of wild North American bats resulting from

158   infection with SARS-CoV-2 or from management actions meant to mitigate transmission,

159   (2) minimizing the risk of SARS-CoV-2 becoming endemic in any North American bat

160   population through sustained bat-to-bat transmission,

161   (3) maintaining or maximizing the ability of WC and WR to carry out their functions for the

162   benefit of humans and wildlife, and

163   (4) maximizing the opportunities for scientific research on bats and within bat habitats.

164

165   For a complete summary of objectives, including the full text of the select objectives presented

166   here, see Runge et al. (2020).

167

168   Based on the agreement in objectives between the first summer assessment and this study, the

169   existing infection risk models developed by Runge et al. (2020) remained useful for estimating

170   risk, but needed to be updated to include new and relevant information. Conceptually, new

171   information from empirical study and experts can reduce critical uncertainties and can be

172   incorporated into the existing Runge et al. (2020) framework as indicated in Figure 1 by the gray,

173   dashed arrows. In the following sections, we describe the three infection risk models for RSM,

174   WR, and WC activity types from the previous assessment and then revise them to include new

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175   information (blue highlighted steps of Figure 1: "New Information (monitoring, research)" and

176   "Update Predictive Models (Learn)"). We then provide updated estimates on bat risk and

177   mitigation in the results that can help to evaluate the consequences of SARS-CoV-2 risk

178   management strategies (Figure 1: "Evaluate Consequences").

179

180   <Insert figure 1 here>

181

182   **RSM Infection Risk Model**

183   The RSM infection risk model was calculated from three encounter types: workers handling bats,

184   workers in proximity to bats in a shared enclosed space, and workers in close proximity to bats

185   but not in a shared enclosed space. The expected number of infected bats resulting from research,

186   survey, or monitoring activities is the sum of the expected number of bats infected through each

187   of the three encounter types:

188
189    $$E\left[I_{sp}^{RSM}\right] = E\left[I_H^{RSM} + I_E^{RSM} + I_P^{RSM}\right] = p_{RSM}^+ (H_{sp}^{RSM}\beta_H^{RSM} + E_{sp}^{RSM}\beta_E^{RSM} + P_{sp}^{RSM}\beta_P^{RSM}]\sigma_{sp}$$
190
191   where
192   I^{RSM} is the number of infected bats through each of three encounter pathways ($H =$
193   handling of bats; $E =$ exposed in a shared enclosed space; $P =$
194   encountered not in an enclosed space)
195   p_{RSM}^+ is the probability that someone conducting RSM work is actively shedding
196   SARS-CoV-2 virus on any given day of the 2021 active season;
197   H_{sp}^{RSM} is the total number of bats handled during the 2021 active season;
198   E_{sp}^{RSM} is the total number of bats exposed in a shared enclosed space, but not
199   handled, during the 2021 active season;
200   P_{sp}^{RSM} is the total number of bats encountered, but not in an enclosed space or
201   handled, over the course of the 2021 active season;
202   β_H^{RSM} is the probability that a bat handled by a RSM scientist who was actively
203   shedding virus would be exposed to the virus (an "exposure
204   probability") in the absence of any new restrictions, regulations, or
205   protocols, taking into account the handling time typical of RSM
206   activities;

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207   β_E^{RSM} is the probability that a bat in an enclosed space within a 6-foot proximity
208   of (but not handled by) a RSM scientist who was actively shedding
209   virus would be exposed to the virus (an "exposure probability") in the
210   absence of any new restrictions, regulations, or protocols;
211   β_P^{RSM} is the probability that a bat **not** in an enclosed space within a 6-foot
212   proximity of (and not handled by) a RSM scientist who was actively
213   shedding virus would be exposed to the virus (an "exposure
214   probability") in the absence of any new restrictions, regulations, or
215   protocols; and
216   σ_{sp} is the species-specific probability that a bat exposed to a sufficient viral
217   dose of SARS-CoV-2 would become infected by the virus (the
218   "probability of susceptibility").
219

220 **Wildlife Rehabilitators Infection Risk Model**

221 The WR infection risk model was calculated from two encounter types: bat handling, and

222 workers in proximity to bats but not in a shared enclosed space. The expected number of infected

223 bats arising from wildlife rehabilitation over the summer season is the sum of the expected

224 number of bats infected through each of the two encounter types:

225
226
$$E\left[I_{sp}^{WR}\right] = E[I_H^{WR} + I_P^{WR}] = p_{WR}^+ (H_{sp}^{WR} \beta_H^{WR} + P_{sp}^{WR} \beta_P^{WR})\sigma_{sp}$$
227

228 where
229   I^{WR} is the number of infected bats through each of three encounter pathways ($H =$
230   handling of bats; $P =$ encountered not in an enclosed space)
231   p_{WR}^+ is the probability that someone conducting rehabilitation work is actively
232   shedding SARS-CoV-2 virus on any given day of the 2021 active
233   season;
234   H_{sp}^{WR} is the total number of bats handled during the 2021 active season;
235   P_{sp}^{WR} is the total number of bats exposed, not in an enclosed space or handled,
236   by wildlife rehabilitators during the 2021 active season;
237   β_H^{WR} is the probability that a bat handled by a WR who was actively shedding
238   virus would be exposed to the virus (an "exposure probability") in the
239   absence of any new restrictions, regulations, or protocols, taking into
240   account the handling time typical of rehab activities;
241   β_P^{WR} is the probability that a bat **not** in an enclosed space within a 6-foot
242   proximity of (and not handled by) a WR who was actively shedding
243   virus would be exposed to the virus (an "exposure probability") in the
244   absence of any new restrictions, regulations, or protocols; and
245   σ_{sp} is the species-specific probability that a bat exposed to a sufficient viral
246   dose of SARS-CoV-2 would become infected by the virus (the
247   "probability of susceptibility").

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249 **Wildlife Control Operators Infection Risk Model**

250 The WC infection risk model is calculated from two encounter types: bat handling, and workers

251 in proximity to bats but not in a shared enclosed space. The expected number of infected bats

252 arising from wildlife control operations over the summer season is the sum of the expected

253 number of bats infected through each of the two encounter types:

254

255
$$E\left[I_{sp}^{WC}\right] = E[I_H^{WC} + I_P^{WC}] = p_{WCO}^+ (H_{sp}^{WC}\beta_H^{WC} + P_{sp}^{WC}\beta_P^{WC})\sigma_{sp}$$

256 where

257   p_{WC}^+ is the probability that someone conducting WC work is actively shedding
258   SARS-CoV-2 virus on any given day of the 2021 active season;
259   H_{sp}^{WC} is the total number of bats handled during the 2021 active season;
260   P_{sp}^{WC} is the total number of bats exposed, but not handled, by WC during the
261   2021 active season;
262   β_H^{WC} is the probability that a bat handled by a WC who was actively shedding
263   virus would be exposed to the virus (an "exposure probability") in the
264   absence of any new restrictions, regulations, or protocols, taking into
265   account the handling time typical of WC activities;
266   β_P^{WC} is the probability that a bat **not** in an enclosed space within a 6-foot
267   proximity of (and not handled by) a WC who was actively shedding
268   virus would be exposed to the virus (an "exposure probability") in the
269   absence of any new restrictions, regulations, or protocols; and
270   σ_{sp} is the species-specific probability that a bat exposed to a sufficient viral
271   dose of SARS-CoV-2 would become infected by the virus (the
272   "probability of susceptibility").

273

274 **Probability that a crew member is positive and shedding virus**

275 We calculated the probability that a crew member is positive and shedding virus as a function of

276 the prevalence of COVID-19 in the surrounding community (ψ), and the sensitivity (Sn) and

277 specificity (Sp) of COVID-19 testing. Sensitivity is the probability that an individual who has

278 COVID-19 tests positive, whereas specificity is the probability that a healthy individual without

279 COVID-19 tests negative. We selected a sensitivity value of 0.70, and specificity of 0.95

280 (Arevalo-Rodriguez et al. 2020; Watson et al. 2020); however, we recognize that these values

281 vary according to the type of test administered. For our risk assessment, we are primarily

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282   interested in the probability that a crew member receives a negative test result but is truly

283   infected with SARS-CoV-2. This probability can be calculated using Bayes' Theorem as:

284

285
$$p^+ = \frac{(1-Sn)\times\psi}{(1-Sn)\times\psi+Sp\times(1-\psi)}.$$

286

287   If a crew member does not take a test, the probability that a crew member is positive and

288   shedding virus can be estimated by the local prevalence, ψ, or by some other method that

289   accounts for the crew member's risk behavior (e.g., https://www.microcovid.org/).

290   **Bat Encounter Types and Exposure Probabilities**

291   To calculate the number of bats handled (H), encountered in an enclosed space (E), or in

292   proximity to workers in an unenclosed space (P), we multiplied the total number of bats

293   encountered in a typical season of work by the percentage of each bat encounter type (Table 1).

294   We used the same encounter estimates reported in Runge et al. (2020), based on reporting data

295   from Colorado Department of Wildlife, Connecticut Department of Energy and Environmental

296   Protection, Kentucky Department of Fish and Wildlife Resources, New York State Department

297   of Environmental Conservation, Oregon Department of Fish and Wildlife, Virginia Department

298   of Game and Inland Fisheries, Wisconsin Department of Natural Resources, USDA Forest

299   Service, National Park Service, U.S. Geological Survey, and the white-nose syndrome national

300   surveillance program. For RSM activities, most bat interactions involve handling (45.8%),

301   followed by activities in proximity to bats (42.7%), and sharing an enclosed space with bats

302   (11.5%). For WR, all documented human bat interactions result from handling (100%). For WC,

303   most human-bat interactions occur when a practitioner comes within 6-feet of a bat (77.1%) but

304   does not handle the bat; the other 22.9% of interactions involve bat handling (Table 1).

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306   <Insert table 1 here>

307

308   For each human-bat activity and encounter type, Runge et al. (2020) used formal expert

309   judgment protocols, notably the IDEA("Investigate, Discuss, Estimate, Aggregate") protocol

310   (Hanea et al. 2017) and the four-point elicitation method (Speirs-Bridge et al. 2010), to estimate

311   unique probabilities of exposure and an associated measure of uncertainty (i.e., β parameters in

312   infection risk model equations). The four-point elicitation method provided a point estimate and

313   a measure of within-expert uncertainty by eliciting each expert's lowest, highest, and best

314   estimates of model parameters as well as an estimate of confidence that their reported values

315   included the true value. The expert panel included a total of 13 individuals with diverse

316   professional experience and expert specializations in wildlife epidemiology, virology, bat

317   physiology, and bat ecology (Runge et al. 2020). Two rounds of elicitation were held, and group

318   meetings in between rounds were used to clarify questions and responses, with the aim of

319   reducing sources of expert bias. To estimate an aggregate expert distribution from individual

320   responses, the parameters that best fit probability distributions to the elicited quantiles from each

321   expert independently were identified. Then parameters for an aggregate distribution were

322   estimated by averaging the independent probability density functions (PDFs) across all experts

323   and finding parameters for a fitted aggregate distribution that minimized the Kullback-Leibler

324   distance (Kullback and Leibler 1951) between the average PDF and the fitted PDF.

325

326   For RSM activities, experts estimated a median of 49.7 bats (80% confidence interval: 15.3,

327   84.3) exposed out of 100 encountered during handling, a median of 19.4 bats (80% CI: 2.2.,

328   72.4) exposed out of 100 encountered when in enclosed space within 6 feet of a SARS-CoV-2

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329   positive scientist, and a median of 6.4 bats (80% CI: 0.6, 43.8) exposed out of 100 within 6 feet

330   of a SARS-CoV-2 positive scientist in an unenclosed space. For WR activities, experts estimated

331   a median of 70.4 bats (80% CI: 24.4, 94.6) exposed out of 100 during handling and a median of

332   24.3 bats (80% CI: 2.8, 78.4) exposed out of 100 when within 6 feet of a SARS-CoV-2 positive

333   wildlife rehabilitator. For WC activities, experts estimated a median of 27.7 bats (80% CI: 3.7,

334   79.2) exposed out of 100 during handling and 9.6 bats (80% CI: 1.0, 53.9) exposed out of 100

335   when within 6 feet of a SARS-CoV-2 positive wildlife control operator.

336

337   In addition to COVID-19 testing for risk mitigation, agencies can issue guidelines for properly

338   fitted PPE use during human-bat interactions. In Runge et al. (2020), the effectiveness of N95

339   respirators for mitigating the risk of SARS-CoV-2 exposure during RSM, WR, and WC activities

340   was evaluated. Following that publication, additional information identified aerosolized virus as

341   the primary pathway of human-to-human disease exposure (Meyerowitz et al. 2020); thus, we

342   can evaluate the ability of other face coverings to reduce viral exposure of bats if we can assume

343   that exposure probabilities from Runge et al. (2020) are reduced by reported filtration

344   efficiencies of other PPE types. Common PPE types include: N95 respirators (percent filtration

345   efficiency (FE) mean ± SD: 99.4 ± 0.2; 3M model 1870), surgical masks (FE: 89.5 ± 2.7), cloth

346   masks (FE: 50.9 ± 16.8), and face shields (FE: 23 ± 3.3) (Davies et al. 2013, Lindsley et al. 2014,

347   Long et al. 2020).

348   **Probability of Susceptibility**

349   We used probability of bat susceptibility (σ_{sp}) estimates that were derived from expert judgment

350   using the same structured protocols described above. In the Cook et al. (2021) application, the

351   expert panel included a diverse group of 12 professionals, 4 of whom participated in the Runge

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352   et al. (2020) study. Similar to the Runge et al. (2020) study, two rounds of elicitation were held,

353   and the probability of susceptibility for little brown bats was estimated using fitted aggregate

354   group distributions based on the 12 expert responses.

355

356   The probability-of-susceptibility estimates, probability of infectious crew members, and

357   effectiveness of PPE were then used to estimate the number of little brown bats that could be

358   infected out of 1000 encountered during RSM, WC, and WR activities. For all comparisons,

359   unless otherwise specified, we assumed that the local COVID-19 prevalence was 0.05. Each

360   infection risk model was simulated 100,000 times to explore uncertainty in the parameters. All

361   analyses were performed in Program R (R Core Team, 2018). All data used in these analyses

362   were provided as electronic records and no vertebrate species were contacted or handled as a

363   direct result of this study.

364   **RESULTS**

365   **Probability of Susceptibility**

366   Conditional on a sufficient dose of SARS-CoV-2 for individual bat infection, the expert panel

367   from Runge et al. (2020) estimated that the median probability of susceptibility for little brown

368   bat was 0.44 (80% PI:0.08 – 0.88). Following the accumulation of new information, a follow-up

369   expert elicitation estimated that the median probability of susceptibility was 89% lower and had

370   less uncertainty (Cook et al. 2021; Figure 2, median probability of susceptibility: 0.05; 80%

371   PI:0.003 – 0.37). The updated estimate was informed, in part, by new information, including

372   human and bat angiotensin-converting enzyme 2 (ACE2) receptor homology (an enzyme that is

373   important to SARS-CoV-2 binding in the host) (Damas et al. 2020), and the availability of lab-

374   based challenge studies (Hall et al. 2020).

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376   <Insert figure 2 here>

377

378   **Baseline risk**

379   We reanalyzed the infection risk models described in Runge et al. (2020) using updated

380   estimates of the probability of susceptibility for little brown bats reported in Cook et al. (2021).

381   We found an 87 – 88% decrease in the median number of bats estimated to be infected per 1000

382   encountered when compared against the earlier results. For RSM activities, the median number

383   of bats infected per 1000 was estimated to be 6.96 in the Runge et al. (2020) assessment (Figure

384   3; 80% CI: 1.85 – 19.41). Using updated probability of susceptibility estimates, we found that

385   the median number of bats estimated to be infected by SARS-CoV-2 was less than one

386   individual per 1000, which is 88% lower than the initial estimate (Figure 3; median: 0.83, 80%

387   CI: 0.07 – 7.82). For WR encounters, the median number of bats infected per 1000 was reduced

388   from 13.03 (Figure 3; 80% CI: 3.54 – 36.14) to 1.56 – a similar 88% decrease in the median

389   value (Figure 3; 80% CI: 0.12 – 14.71). For WC encounters, the median number of bats infected

390   per 1000 was reduced from 3.72 (Figure 3; 80% CI: 0.84 – 14.43) to 0.47 – an 87% decrease in

391   the median value (Figure 3; 80% CI: 0.03 – 4.79).

392

393   <Insert figure 3 here>

394

395   We also analyzed the baseline bat infection risk across three different levels of COVID-19

396   prevalence (Figure S.1). For RSM activities, the median number of bats infected per 1000

397   encountered fell from a median of 0.83 (80% CI: 0.07 – 7.82) when COVID-19 prevalence was

398   0.05, to a median of 0.15 (80% CI: 0.01 – 1.29) and 0.015 (80% CI: 0.001 – 0.129) when

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399 COVID-19 prevalence was 0.01 and 0.001, respectively. For WR activities, the median number

400 of bats infected per 1000 fell from a median of 1.56 (80% CI: 0.12 – 14.71) when COVID-19

401 prevalence was 0.05, to a median of 0.27 (80% CI: 0.02 – 2.34) and 0.027 (80% CI: 0.002 –

402 0.23) when COVID-19 prevalence was 0.01 and 0.001, respectively. For WC activities, the

403 median number of bats infected per 1000 fell from a median of 0.47 (80% CI: 0.03 – 4.79) when

404 COVID-19 prevalence was 0.05, to a median of 0.08 (80% CI: 0.005 – 0.76) and 0.008 (80% CI:

405 0.0005 – 0.08) when COVID-19 prevalence was 0.01 and 0.001, respectively.

406 **Risk mitigation**

407 We used the updated parameter estimates to evaluate the effectiveness of PPE and pre-survey

408 COVID-19 testing of personnel for reducing baseline estimates of bat infections per 1000

409 encountered (Figures 4 and 5). We found that N95 respirators reduced the median estimates of

410 infection by 95 – 96% for all three encounter types (i.e., RSM, WR, and WC work), when

411 compared against median values with updated parameter estimates and without enhanced

412 personal protective equipment (Figure 4A – C; overall reduction of 99% from Runge et al.

413 2020). For surgical masks, we found an 89% reduction in the median estimate of infection for all

414 three encounter types (i.e., RSM, WR, and WC work; Figure 4A – C), when compared against

415 median values with updated parameter estimates and without enhanced personal protective

416 equipment. For cloth masks, we found a reduced median estimate of infection of 54 – 55% for all

417 three encounter types (Figure 4A – C), when compared against median values with updated

418 parameter estimates and without enhanced personal protective equipment. Finally, for face

419 shields, we found a reduced median estimate of infection of 22 – 24% for all three encounter

420 types (Figure 4A – C), when compared against median values with updated parameter estimates

421 and without enhanced personal protective equipment.

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422

423   <Insert figure 4 here>

424

425   For COVID-19 testing, we found that the median estimate of the number of SARS-CoV-2

426   infected bats decreased by 65 – 67% across all three encounter types, as a result of a negative test

427   of field crew 3 days prior to bat handling (overall reduction of 88 – 89% from the Runge et al.

428   2020 assessment; Figure 5).

429

430   <Insert figure 5 here>

431

432   **DISCUSSION**

433   The existing decision framework developed in Runge et al. (2020) allowed for a rapid re-

434   evaluation of human-to-bat SARS-CoV-2 transmission risk during summer fieldwork based on

435   new knowledge included in Cook et al. (2021), expert judgment, and other empirical studies. We

436   found that new knowledge substantially reduced uncertainty, lowered risk estimates, and

437   provided additional management alternatives that may be important to preventing SARS-CoV-2

438   infection in bats during RSM, WC, and WR activities. More broadly, we found that decision

439   analysis coupled with expert judgment provided substantial benefits across all three studies (i.e.,

440   Runge et al. 2020, Cook et al. 2021, this study) and we expect that these benefits transcend

441   SARS-CoV-2 to other wildlife disease systems. In particular, decision analysis helped to identify

442   the fundamental management objectives, specify the possible alternatives, direct the

443   development of quantitative infection risk models, and ultimately, create a risk assessment

444   framework that remained useful over time and as our knowledge of the novel pathogen system

445   improved. Formal expert judgment allowed us to estimate parameters with the available

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446   information in a timely manner, without having to initiate and wait for the results of new

447   empirical studies.

448

449   We found that the median numbers of little brown bats potentially infected during summer RSM,

450   WC, and WR activities were reduced substantially from those reported in the initial risk

451   assessment by Runge et al. (2020), in part because an expanded range of management

452   alternatives were available to further reduce these risks. By expanding the range of management

453   alternatives for preventing transmission, we provide decision makers with additional options

454   (and estimates of their effect on the number of infected bats) that may allow for some research

455   and management activities to resume. For example, if the baseline risk of an activity exceeds an

456   agency's tolerance for risk, they may choose to require the use of facemasks or COVID-19

457   testing prior to human-bat encounters. However, COVID-19 testing may be difficult to

458   implement in certain situations, especially for WC and WR activities that often arise

459   spontaneously rather than from advanced planning. As an alternative, other forms of mitigation

460   may be called for, and our assessment provides measures of risk across a range of potentially

461   suitable mitigation measures. It is also important to note that risk tolerance may differ among

462   agencies, and thus the response to the same risk may differ markedly in the decisions made (Sells

463   et al. 2016).

464

465   Across the three risk assessments (Runge et al. 2020, Cook et al. 2021, this study), expert

466   judgment was critical to our ability to rapidly estimate risks associated with SARS-CoV-2. At

467   the time of Runge et al. (2020) and Cook et al. (2021), there were no data from empirical studies

468   available to directly inform little brown bat SARS-CoV-2 susceptibility. Instead, structured

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469   protocols were implemented that derived unknown parameter estimates using leading experts in

470   relevant fields of study. Expert judgment has gained credibility across a diversity of decision-

471   making applications because it provides a viable alternative when empirical data are not yet

472   available for generating unknown parameter estimates (Tyshenko et al. 2016; Bianchini et al.

473   2020), quantifying uncertainty (McBride et al. 2012; Conroy and Peterson 2013), and controlling

474   for sources of bias (McBride et al. 2012). We found expert elicitation to be particularly powerful

475   for our assessments because it allowed us to rapidly integrate the best available science and

476   knowledge and provide guidance to managers dealing with uncertain but immediate risks to

477   North American bats.

478

479   While decision framing, expert judgment, and the development of a quantitative infection risk

480   model assisted in the production of decision-relevant science, the timely release of our results to

481   support decision-making remained a challenge. Across the first two studies, the production of

482   science happened over the course of several weeks, including several rounds of agency

483   consultation and the development of quantitative infection risk models. For information sharing,

484   we were able to provide the results to decision makers in a timely fashion through briefings after

485   we had peer review and agency clearance, but before the results were published. The agencies,

486   however, were also interested in timely publication, so they could cite the research when

487   communicating their decisions to the public. In total, the documentation, external peer-review,

488   and publication process added an additional 5.5 weeks for Runge et al. (2020) and 11.5 weeks

489   for Cook et al. (2021). While these timelines are typical and generally necessary for rigorous

490   peer review, shorter timelines for studies evaluating emergent wildlife disease risks could be

491   helpful because the decisions they are intended to inform may be necessary before completion of

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492   a standard peer-review and publication process. While it is not our intention to criticize any

493   journal, reviewers, or peer-review process, we recognize that the production of decision-relevant

494   science using decision analysis, quantitative modeling, and undergoing a full peer-review

495   process may benefit from shorter timelines to provide information needed for urgent agency

496   decisions .

497

498   There are likely many options to improve the timely delivery of science to support urgent

499   wildlife disease management decisions moving forward, and we provide a few suggestions that

500   may be useful. First, it may be useful for journals to consider creating alternate production tracks

501   that can expedite the review and publication process and provide timely results at the speed of

502   agency decisions. Alternative options for distribution, such as preprint servers (like bioRxiv and

503   medRxiv) have already become critical avenues for timely release of information during the

504   COVID-19 pandemic; however, these avenues do not address the critical role that peer-review

505   plays in the production of reliable science. Second, for agencies that frequently make urgent

506   decisions and that currently rely only on published results to communicate scientific support for

507   those decisions to the public, it may be beneficial to consider using external science review

508   boards that can provide objective evaluations of unpublished findings for formal consideration in

509   time-sensitive decision-making. Lastly, dedicated risk assessment teams that produce rapid

510   qualitative assessments of wildlife disease risks within hours or days of an identified novel

511   hazard would be helpful. While other, more qualitative, assessments may be based on

512   preliminary results and limited knowledge that is subject to considerable change, they can be

513   effective as a bridge to more rigorous assessments that include agency consultation, quantitative

514   modeling, and the evaluation of management alternatives. Nevertheless, we hope that our risk

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515   assessments may serve as a model to assess threats that SARS-CoV-2 continues to present to

516   wildlife, and that a larger discussion be stimulated to identify the best approaches to deliver

517   decision-relevant science for emerging wildlife diseases on timescales that matter.

518

519   Moving forward, it will be possible to update future SARS-CoV-2 risk assessments as

520   knowledge of the critical uncertainties improves. Currently there are several variants of the

521   SARS-CoV-2 pathogen circulating in the human population that have the potential to alter the

522   transmissibility of the virus for humans and may affect the susceptibility of wildlife species to

523   the virus. There are widespread vaccination efforts occurring that will also reduce the localized

524   risk that workers are infectious at the time of bat encounters. At the local level, vaccinations are

525   likely to decrease the prevalence of COVID-19, ultimately reducing SARS-CoV-2 transmission

526   risk to bats (Figure S.1). At the individual level, COVID-19 vaccines are effective at preventing

527   human infection (median: 66.3% [95% confidence interval (CI): 59.9%–71.8%] effective for

528   preventing symptomatic, lab confirmed cases 14 days post-immunization for Johnson & Johnson

529   vaccine [Oliver et al. 2021], and median: 90% [95% CI: 68%–97%] effective for preventing all

530   cases regardless of symptoms 14 days post-immunization for Pfizer mRNA vaccine [Thompson

531   et al. 2021]); however, there remain unknowns surrounding the period of immunity and its

532   efficacy against newly emerging viral strains. More information should be available in coming

533   months on the duration of protection from vaccine and the potential for individuals with

534   "breakthrough" infections to shed virus. As our knowledge continues to improve surrounding

535   SARS-CoV-2 and the risks it presents to bats, these factors, as well as other relevant information,

536   could be included in future assessments to ensure that agencies have the best available

537   information for making decisions.

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660 **Table 1.** Fraction of bats encountered through each of three encounter types for each of three
661 activities. The three encounter types are: handling; encounter within 6 feet in an enclosed space;
662 and proximity within 6 feet in an unenclosed space. The data were gathered from the following
663 agencies: Colorado Department of Wildlife, Connecticut Department of Energy and
664 Environmental Protection, Kentucky Department of Fish and Wildlife Resources, New York
665 State Department of Environmental Conservation, Oregon Department of Fish and Wildlife,
666 Virginia Department of Game and Inland Fisheries, Wisconsin Department of Natural
667 Resources, Forest Service, National Park Service, U.S. Geological Survey, and the White-Nose
668 surveillance program (Runge et al. 2020).

669

	Research, survey, monitoring and management			Wildlife rehabilitation		Wildlife Control	
	Handling	Enclosed	Proximity	Handling	Proximity	Handling	Proximity
Total bats	8642	2172	8056	1459	0	447	1502
Encounter perc. (%)	45.8	11.5	42.7	100	0	22.9	77.1

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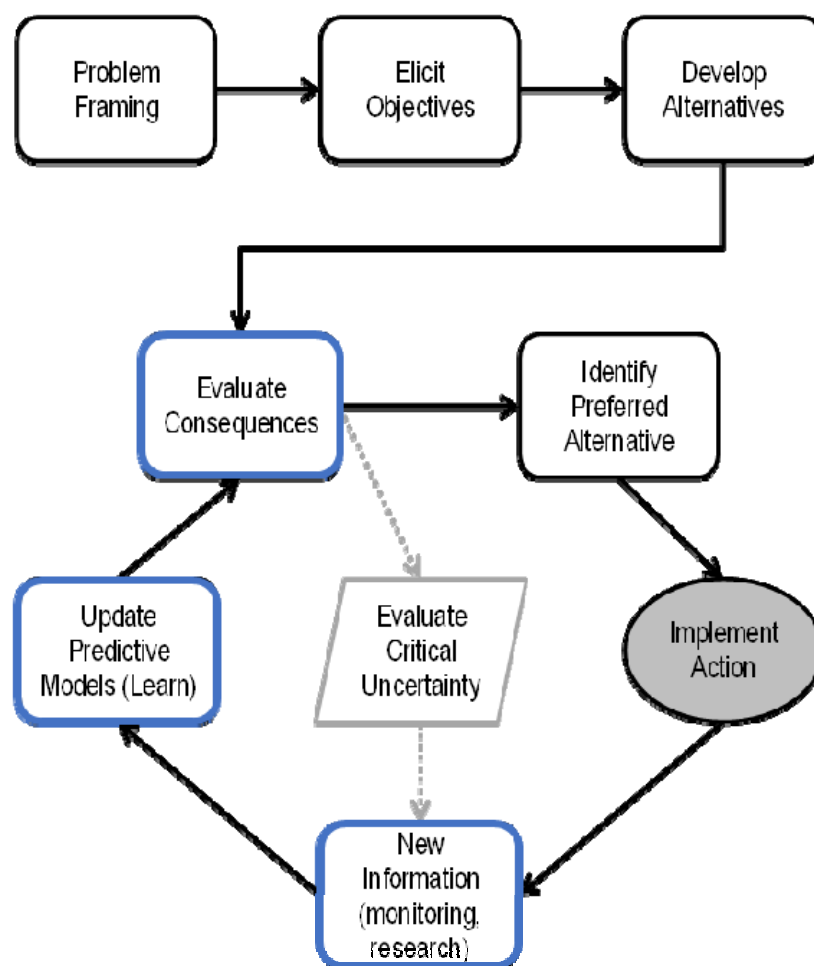699

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703 **Figure 1.** Steps of decision analysis, including the option to revisit consequences based on newly
704 generated knowledge or data. In April 2020, Runge et al. (2020) worked with state and federal
705 decision makers to frame the decision and produce risk estimates that were useful to guide
706 management actions (Runge et al. 2020). Based on new knowledge and data that evaluated
707 critical uncertainties from Runge et al. (2020) (gray dashed arrows and central gray outlined
708 polygon), we revisited several steps (boxes outlined in blue) to rapidly re-evaluate the risk of
709 SARS-CoV-2 transmission during summer RSM, WC, and WR activities. Frequently updating
710 risk assessments using the best available science may help decision makers implement actions
711 that best achieve management objectives (gray filled oval). Adapted from Runge (2011).
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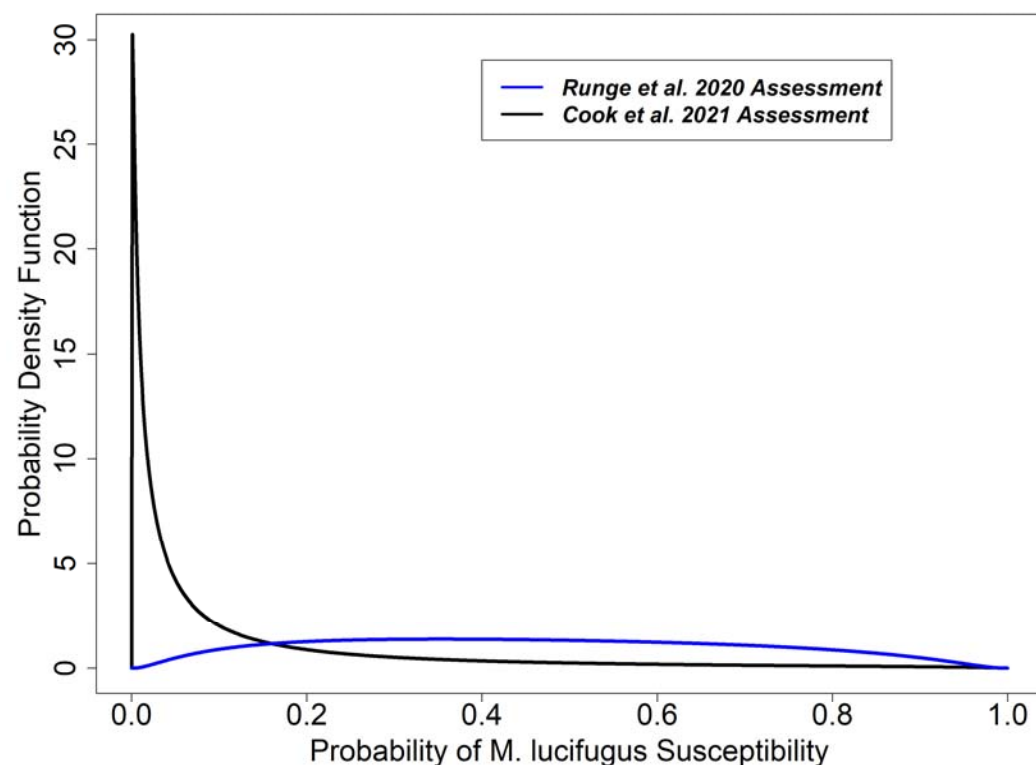
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Figure 2. Comparison of probability of susceptibility estimates for little brown bat from Runge et al. (2020) (blue line) and from Cook et al. (2021) (black line).Experts estimated that the median probability of susceptibility was 89% lower based on updated knowledge gathered from bat challenge studies, ACE2 homology between humans and bats, and other sources (Cook et al. 2021).
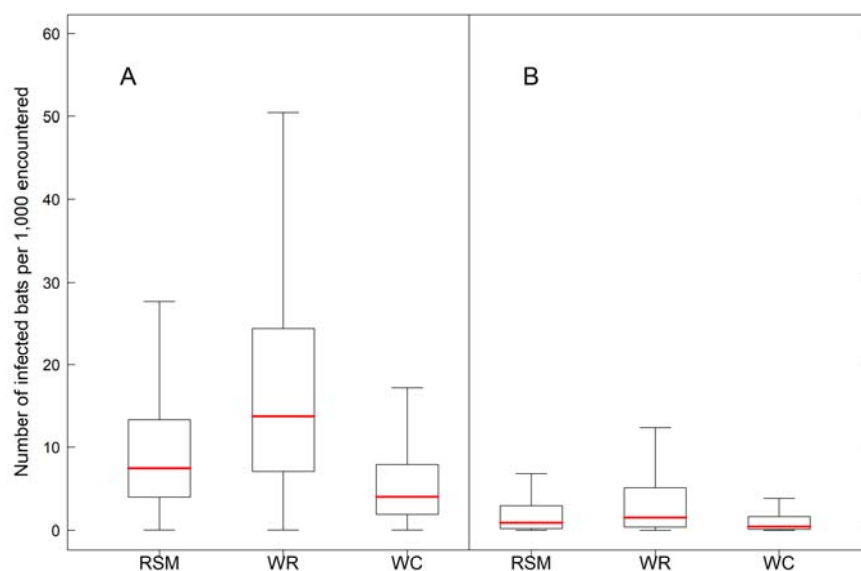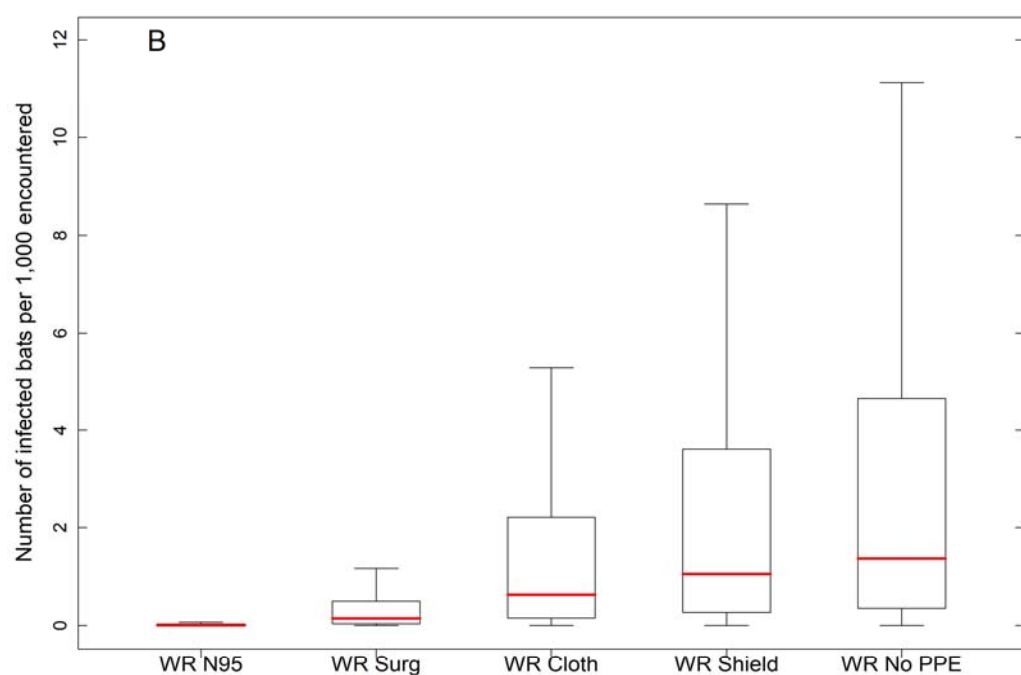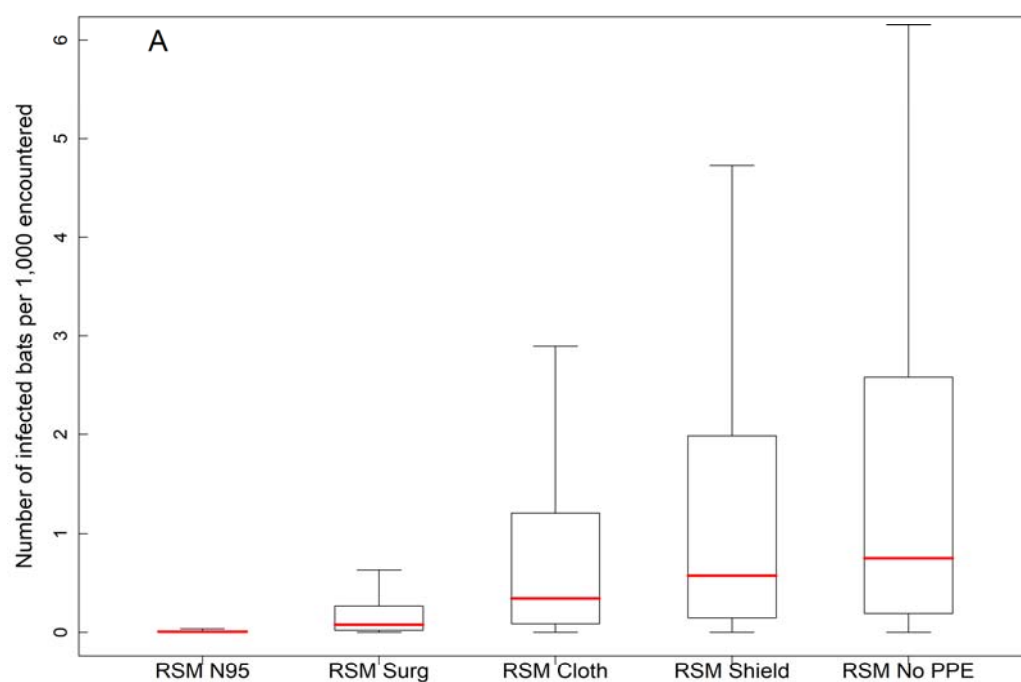
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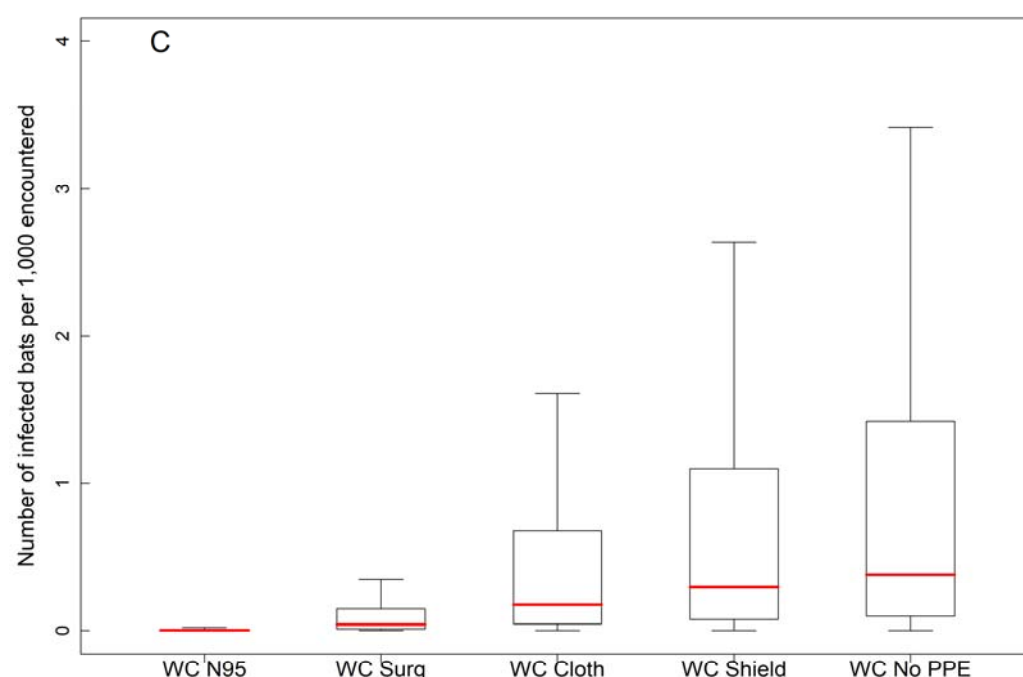
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757 **Figure 3.** Number of bats per 1,000 exposed to and infected by SARS-CoV-2 by the three
758 transmission pathways. RSM=research, survey, monitoring, and management activities; WR=
759 wildlife rehabilitation; WC= wildlife control operations. Boxplot whiskers represent 99%
760 prediction interval. For comparisons, we used the same assumed ratio of encounter modes
761 (handling, enclosure, and proximity) and probability of worker shedding SARS-CoV-2 (median:
762 0.057; 80% interval: 0.022-0.112) from Runge et al. (2020). **(A)** Results reproduced based on
763 expert-elicited data on probability of bat susceptibility from Runge et al. (2020) assessment. **(B)**
764 Results based on parameter values from December 2020 assessment.

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Figure 4. Number of bats per 1,000 exposed to and infected by SARS-CoV-2 by the three transmission pathways. RSM=research, survey, monitoring, and management activities; WR= wildlife rehabilitation; WC= wildlife control operations. Boxplot whiskers represent 99% prediction interval. We used the same assumed ratio of encounter modes (handling, enclosure, and proximity) from Runge et al. (2020). Results based on expert elicited data on probability of bat susceptibility from the Cook et al. (2021) assessment. **(A)** Effectiveness of PPE compared against baseline estimates for RSM activities. **(B)** Effectiveness of PPE compared against baseline estimates for WR activities. **(C)** Effectiveness of PPE compared against baseline estimates for WC activities.

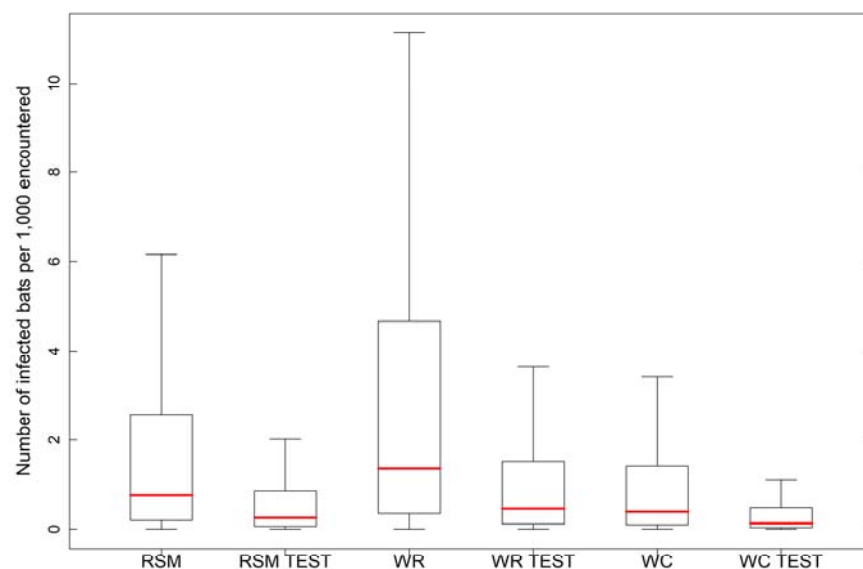[1] *Email:* jcook@usgs.gov

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Figure 5. Number of bats per 1,000 exposed to and infected by SARS-CoV-2 by the three
transmission pathways with and without pre-survey COVID-19 testing. RSM=research, survey,
monitoring, and management activities; WR= wildlife rehabilitation; WC= wildlife control
operations. Boxplot whiskers represent 99% prediction interval. We used the same assumed ratio
of encounter modes (handling, enclosure, and proximity) from Runge et al. (2020). Results based
on expert elicited data on probability of bat susceptibility from Cook et al. (2021) assessment.

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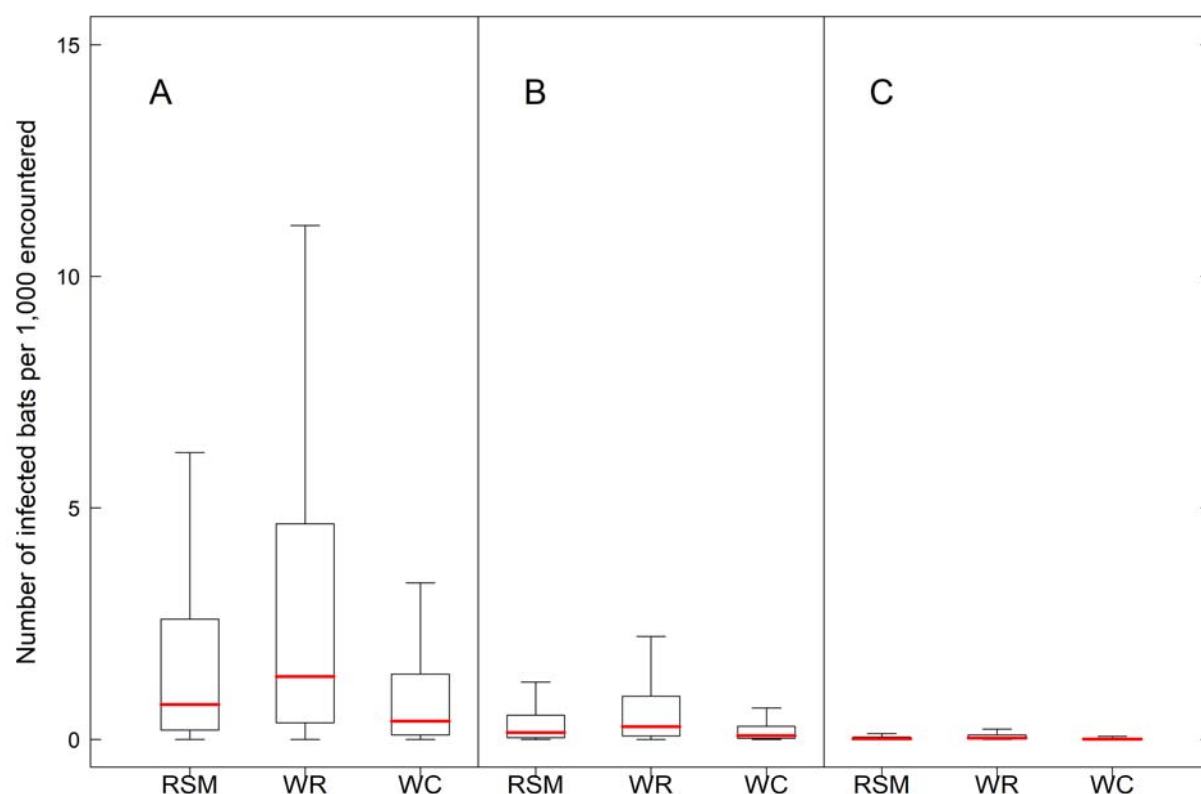820 **Supplementary Figure**

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823 **Figure S.1.** Comparison of the number of bats per 1,000 exposed to and infected by SARS-CoV-
824 2 by the three transmission pathways and across 3 community prevalence levels: 0.05, 0.01, and
825 0.001. RSM, research, survey, monitoring, and management activities; WR, wildlife
826 rehabilitation; WC, wildlife control operations. Boxplot whiskers represent 99% prediction
827 intervals. We used the same assumed ratio of encounter modes (handling, enclosure, and
828 proximity) from Runge et al. (2020). Results based on expert elicited data on probability of bat
829 susceptibility from Cook et al. (2021) assessment. **(A)** Number of bats infected at county-level
830 COVID-19 prevalence of 0.05. **(B)** Number of bats infected at county-level COVID-19
831 prevalence of 0.01. **(C)** Number of bats infected at county-level COVID-19 prevalence of 0.001.

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