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# **RESEARCH ARTICLE**



# **Evaluating the risk of SARS-CoV-2 transmission** to bats in the context of wildlife research. rehabilitation, and control

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# Abstract

Preventing wildlife disease outbreaks is a priority for natural resource agencies, and management decisions can be urgent, especially in epidemic circumstances. With the emergence of SARS-CoV-2, wildlife agencies were concerned whether the activities they authorize might increase the risk of viral transmission from humans to North American bats, but had a limited amount of time in which to make decisions. We describe how decision analysis provides a powerful framework to analyze and reanalyze complex natural resource management problems as knowledge evolves. Coupled with expert judgment and avenues for the rapid release of information, risk assessment can provide timely scientific information for evolving decisions. In April 2020, the first rapid risk assessment was conducted to evaluate the risk of transmission of SARS-CoV-2 from humans to North American bats. Based on the best available information and relying heavily on expert judgment, the risk assessment found a small possibility of transmission during summer work activities. Following that assessment, additional knowledge and data emerged, such as bat viral challenge studies, that further elucidated the risks of humanto-bat transmission and culminated in a second risk assessment in the fall of 2020. We updated the first SARS-CoV-2 risk assessment with new management alternatives and new estimates of little brown bat (Myotis lucifugus) susceptibility, using

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findings from the fall 2020 assessment and other empirical studies. We found that new knowledge led to an 88% decrease in the median number of bats estimated to be infected per 1,000 encountered when compared to earlier results. The use of facemasks during, or a negative COVID-19 test or vaccination prior to, bat encounters further reduced those risks. Using a combination of decision analysis, expert judgment, rapid risk assessment, and efficient modes of information distribution, we provided timely science-based support to decision makers for summer bat work in North America.

#### KEYWORDS

bats, expert judgment, risk analysis, SARS-CoV-2, structured decision making, zoonosis

The emergence of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) occurred in late 2019 and quickly presented immediate and apparent health risks to humans worldwide. By January 2022, coronavirus disease (COVID-19) had resulted in over 301 million documented human cases and over 5.4 million deaths globally (Dong et al. 2020; https:// coronavirus.jhu.edu/, accessed 3 Mar 2022). Although the human health risks of COVID-19 are clear, empirical information on the risk to wildlife is less available, and there remains concern among North American natural resource managers for the potential for SARS-CoV-2 to be transmitted to wildlife from infected humans. Bats are a group of primary focus, following the detection of a closely related betacoronavirus in a horseshoe bat (*Rhinolophus affinis*) in eastern Asia (Olival et al. 2020); however, empirical study to directly assess the threat that SARS-CoV-2 presents to bats remains limited. Further, there is limited knowledge on the evolution of SARS-CoV-2 in wildlife hosts and the role that intermediate hosts may have in its emergence in humans, both initially and over time. Thus, there is an ongoing need for formal risk assessments that can best integrate existing knowledge and uncertainty and guide pressing management decisions regarding activities that require human-bat interaction.

When first confronted with the potential for SARS-CoV-2 exposure and infection in North American (NA) bats, natural resource managers had a limited suite of options to reduce the associated risk, including proceeding as usual with minimal restrictions, placing a moratorium on all work under their authority that may elevate risk, or adopting risk mitigation actions. However, justification for selecting any action was challenged by uncertainty. A few of the most pressing uncertainties surrounded bat species susceptibility, dominant transmission pathways, and the relative exposure and transmission risk of different human-bat interactions. Decisions had to be made without waiting for research that could reduce these uncertainties. Thus, a series of rapid risk assessments were performed using a decision-making approach that helped to: (1) identify agency objectives; (2) guide the development of quantitative models that were explicitly linked to agency objectives; (3) maximize the utility of available data and knowledge; and (4) assess management alternatives under dynamic and frequently changing conditions.

In April 2020, a first assessment was completed that evaluated human-to-bat transmission risk during summer activities (Runge et al. 2020). The assessment was guided by structured decision making and an interagency team. The team specified their objectives, articulated uncertainties, and developed a risk model that explicitly linked objectives to mitigation actions (Runge et al. 2020). The focal species was the little brown bat (*Myotis lucifugus*; LBB) and risks associated with conducting research, survey, monitoring, management (RSM), wildlife rehabilitation (WR), and wildlife control (WC) activities during spring and summer seasons were assessed. The RSM activities of concern were those that put scientists in close proximity to bats during the study of white-nose syndrome (WNS; Hoyt et al. 2019), a fungal disease that has caused declines of over 90% in affected LBB populations (Cheng et al. 2021). Wildlife control

(WC) and rehabilitation (WR) activities were also considered because of the proximity required for the removal and exclusion of bats from dwellings and the care of injured bats. Most information was derived from a formal process of expert judgment, as empirical data were largely unavailable at the time.

The first assessment estimated a non-negligible risk of SARS-CoV-2 transmission from humans to bats (Runge et al. 2020). The risk could be reduced by well-fitted, non-vented N95 respirators (a type of mechanical filter capable of removing viral particles from exhaled breath of infectious individuals) and other protective clothing. In the analysis, critical uncertainties remained—most notably in estimates of the probability of bat susceptibility. The authors noted that the decision framework, complete with objectives, risk model, and management alternatives (e.g., mandating use of N95 respirators), could be rapidly updated as empirical information was gained.

In the fall of 2020, another assessment estimated human-to-bat transmission potential during winter research activities (Cook et al. 2021). Winter activities primarily occur in enclosed spaces, such as hibernacula and winter roosts, which could increase the risk of human-to-bat exposure. The Cook et al. (2021) assessment included new data on the effectiveness of facemasks to reduce viral emission from infectious humans, and new knowledge on bat susceptibility to SARS-CoV-2. Importantly, by the second assessment 2 bat challenge studies were completed; one found no viable SARS-CoV-2 infection in big brown bats (*Epstesicus fuscus*) and the other found that Egyptian fruit bats (*Rousettus aegyptiacus*) were susceptible to the virus (Hall et al. 2020, Schlottau et al. 2020). Other studies on species-specific angiotensin-converting enzyme 2 (ACE2) sequences, an indicator of viral binding potential, shed further light on bat susceptibility of susceptibility for several bat species, including LBB (Cook et al. 2021). New information about human disease transmission and the effectiveness of personal protective equipment (PPE) and COVID-19 testing for preventing exposure was also found to reduce risk.

In early 2021, as we transitioned into another northern hemisphere summer, new data and knowledge had provided sufficient justification to revisit the initial summer assessment. Beginning in May 2021, the widespread availability of vaccines to prevent COVID-19 infection provided another management alternative to reduce the likelihood of human viral shedding. In the current paper, our objective was to update risk estimates for summertime RSM, WC, and WR activities. We first confirm that the structural elements of the decision framing from Runge et al. (2020) remain relevant to agencies considering summer bat work and then update probability of susceptibility estimates for LBB based on Cook et al. (2021). Finally, we re-evaluate the risk of SARS-CoV-2 human-to-bat transmission during summertime RSM, WC, and WR activities and assess the effectiveness of new and existing risk mitigation strategies.

# METHODS

#### Decision framing and general approach

The initial decision framing for human-to-bat SARS-CoV-2 transmission risk formed the basis of results in Runge et al. (2020) and Cook et al. (2021). A diverse group of United States state and federal decision makers were involved in the framing, and as a result, it captured many of the objectives and management alternatives under consideration at the time. The framing of a decision may change over time and can lead to different structuring of the problem and resulting models. Therefore, to update the summer risk assessment we first revisited the original decision framing for spring and summer work with the original decision makers from Runge et al. (2020). During our meetings, agency participants indicated that the decision context and all objectives remained the same. Of relevance to the current assessment were objectives related to the following:

 minimizing the morbidity and mortality of wild NA bats resulting from infection with SARS-CoV-2 or from management actions meant to mitigate transmission,



**FIGURE 1** Steps of decision analysis, including the option to revisit consequences based on newly generated knowledge or data. In April 2020, Runge et al. (2020) worked with state and federal decision makers to frame the decision and produce risk estimates that were useful to guide management actions (Runge et al. 2020). Based on new knowledge and data that evaluated critical uncertainties from Runge et al. (2020; gray dashed arrows and central gray outlined polygon), we revisited several steps (boxes outlined in blue) to rapidly re-evaluate the risk of SARS-CoV-2 transmission during summer RSM, WC, and WR activities. RSM = research, survey, monitoring, or management activities; WR = wildlife rehabilitation; WC = wildlife control operations. Frequently updating risk assessments using the best available science may help decision makers implement actions that best achieve management objectives (gray filled oval). Adapted from Runge (2011).

- minimizing the risk of SARS-CoV-2 becoming endemic in any North American bat population through sustained bat-to-bat transmission,
- (3) maintaining or maximizing the ability of WC and WR to carry out their functions for the benefit of humans and wildlife, and
- (4) maximizing the opportunities for scientific research on bats and within bat habitats.

For a complete summary of objectives, including the full text of these select objectives, see Runge et al. (2020).

Based on the agreement in framing and objectives between the first summer assessment and this study, the existing infection risk models developed by Runge et al. (2020) remained useful but needed to be updated to include new and relevant information, most notably the availability of vaccination as a mitigation strategy. In the following sections, we describe the 3 infection risk models for RSM, WR, and WC activity types and then revise them to include new information (Figure 1; figure adapted from Runge et al. 2011). We then provide updated estimates on bat risk and mitigation that can help evaluate the consequences of SARS-CoV-2 risk management strategies.

## Research, survey, monitoring, or management infection risk model

The RSM infection risk model was calculated from 3 encounter types: workers handling bats, workers in proximity to bats in a shared enclosed space, and workers in proximity to bats but not in a shared enclosed space.

The expected number of infected bats resulting from RSM activities is the sum of the expected number of bats infected through each of the 3 encounter types:

$$E\left[I_{sp}^{RSM}\right] = E\left[I_{H}^{RSM} + I_{E}^{RSM} + I_{P}^{RSM}\right] = p_{RSM}^{+} \left(H_{sp}^{RSM}\beta_{H}^{RSM} + E_{sp}^{RSM}\beta_{E}^{RSM} + P_{sp}^{RSM}\beta_{P}^{RSM}\right)\sigma_{sp}$$

## where

- $I_{.}^{RSM}$  is the number of infected bats through each of 3 encounter pathways (*H* = handling of bats; *E* = exposed in a shared enclosed space; *P* = encountered not in an enclosed space);
- $p_{RSM}^+$  is the probability that someone conducting RSM work is actively shedding SARS-CoV-2 virus on any given day of the 2021 active season;
- $H_{sp}^{RSM}$  is the total number of bats handled during the 2021 active season;
- $E_{sp}^{RSM}$  is the total number of bats exposed in a shared enclosed space, but not handled, during the 2021 active season;
- $P_{sp}^{RSM}$  is the total number of bats encountered, but not in an enclosed space or handled, over the course of the 2021 active season;
- $\beta_{\rm H}^{\rm RSM}$  is the probability that a bat handled by a RSM scientist who was actively shedding virus would be exposed to the virus (an exposure probability) in the absence of any new restrictions, regulations, or protocols, taking into account the handling time typical of RSM activities;
- $\beta_E^{RSM}$  is the probability that a bat in an enclosed space within a 6-foot proximity of (but not handled by) a RSM scientist who was actively shedding virus would be exposed to the virus (an exposure probability) in the absence of any new restrictions, regulations, or protocols;
- $\beta_p^{RSM}$  is the probability that a bat not in an enclosed space within a 6-foot proximity of (and not handled by) a RSM scientist who was actively shedding virus would be exposed to the virus (an exposure probability) in the absence of any new restrictions, regulations, or protocols; and
- $\sigma_{sp}$  is the species-specific probability that a bat exposed to a sufficient viral dose of SARS-CoV-2 would become infected by the virus (the probability of susceptibility).

## Wildlife rehabilitation infection risk model

The WR infection risk model was calculated from 2 encounter types: bat handling and workers in proximity to bats but not in a shared enclosed space. The expected number of infected bats arising from WR over the summer season is the sum of the expected number of bats infected through each of the 2 encounter types:

$$E\left[I_{sp}^{WR}\right] = E\left[I_{H}^{WR} + I_{P}^{WR}\right] = p_{WR}^{+} \left(H_{sp}^{WR}\beta_{H}^{WR} + P_{sp}^{WR}\beta_{P}^{WR}\right)\sigma_{sp}$$

#### where

- $I_{.}^{WR}$  is the number of infected bats through each of 3 encounter pathways (*H* = handling of bats; *P* = encountered not in an enclosed space);
- $p_{WR}^+$  is the probability that someone conducting rehabilitation work is actively shedding SARS-CoV-2 virus on any given day of the 2021 active season;
- $H_{sp}^{WR}$  is the total number of bats handled during the 2021 active season;
- $P_{sp}^{WR}$  is the total number of bats exposed, not in an enclosed space or handled, by wildlife rehabilitators during the 2021 active season;

- $\beta_{H}^{WR}$  is the probability that a bat handled by a WR who was actively shedding virus would be exposed to the virus (an exposure probability) in the absence of any new restrictions, regulations, or protocols, taking into account the handling time typical of rehab activities;
- $\beta_{P}^{WR}$  is the probability that a bat not in an enclosed space within a 6-foot proximity of (and not handled by) a WR who was actively shedding virus would be exposed to the virus (an exposure probability) in the absence of any new restrictions, regulations, or protocols; and
- $\sigma_{sp}$  is the species-specific probability that a bat exposed to a sufficient viral dose of SARS-CoV-2 would become infected by the virus (the probability of susceptibility).

# Wildlife control infection risk model

The WC infection risk model is calculated from 2 encounter types: bat handling and workers in proximity to bats but not in a shared enclosed space. The expected number of infected bats arising from WC operations over the summer season is the sum of the expected number of bats infected through each of the 2 encounter types:

$$E\left[I_{sp}^{WC}\right] = E\left[I_{H}^{WC} + I_{P}^{WC}\right] = p_{WC}^{+}\left(H_{sp}^{WC}\beta_{H}^{WC} + P_{sp}^{WC}\beta_{P}^{WC}\right)\sigma_{sp}$$

where

 $p_{WC}^+$  is the probability that someone conducting WC work is actively shedding SARS-CoV-2 virus on any given day of the 2021 active season:

 $H_{sp}^{WC}$  is the total number of bats handled during the 2021 active season;

- $P_{sp}^{WC}$  is the total number of bats exposed, but not handled, by WC during the 2021 active season;
- $\beta_{\rm H}^{\rm WC}$  is the probability that a bat handled by a WC who was actively shedding virus would be exposed to the virus (an exposure probability) in the absence of any new restrictions, regulations, or protocols, taking into account the handling time typical of WC activities;
- $\beta_P^{WC}$  is the probability that a bat not in an enclosed space within a 6-foot proximity of (and not handled by) a WC who was actively shedding virus would be exposed to the virus (an exposure probability) in the absence of any new restrictions, regulations, or protocols; and
- $\sigma_{sp}$  is the species-specific probability that a bat exposed to a sufficient viral dose of SARS-CoV-2 would become infected by the virus (the probability of susceptibility).

## Probability that a crew member is positive and shedding virus

We calculated the probability that a crew member is positive and shedding virus as a function of the prevalence of COVID-19 in the surrounding community, whether that worker has been vaccinated, and whether they have received a negative COVID-19 test prior to coming into proximity to bats.

For COVID-19 testing, we used published values on the sensitivity (*Sn*) and specificity (*Sp*) of reverse transcription-polymerase chain reaction (RT-PCR) COVID-19 tests and assumed that appropriate testing protocols were followed to maximize the likelihood of an accurate diagnosis. Sensitivity is the probability that an individual who has COVID-19 tests positive, whereas specificity is the probability that an individual without COVID-19 tests negative. We selected a sensitivity value of 0.70, and specificity of 0.95 (Arevalo-Rodriguez et al. 2020, Watson et al. 2020); however, we recognized that these values vary according to the type of test administered. For our risk assessment, we were primarily interested in the probability that a crew member received a negative test result but

is truly infected with SARS-CoV-2. The probability of that a crew member is infected with SARS-CoV-2 but receives a negative test result can be calculated using Bayes' Theorem as:

$$p_{test}^{+} = \frac{(1 - Sn) \times \psi}{(1 - Sn) \times \psi + Sp \times (1 - \psi)}$$

For COVID-19 vaccination, we used a combined vaccine effectiveness ( $V_E$ ) on symptomatic infection with the Delta strain in an age-adjusted adult population for the 2 mRNA vaccines widely available in the United States (COMIRNATY by Pfizer/BioNTech, New York, NY, USA; Spikevax by Moderna, Cambridge, MA, USA), without accounting for waning efficacy (considering how close the summer 2021 field season was to initial vaccination). We fit a normal distribution using quantile matching on the averaged point estimates (93%) and 95-percent confidence intervals (89%–97%) and truncated the fitted distribution at 0 and 1. Thus, we specified  $V_E$  as follows:

$$V_{\rm E} \sim {\rm truncN}(\mu = 0.93, \sigma^2 = 0.03).$$

We also estimated the ability of mRNA vaccines to reduce risk of human-to-bat spillover across a range of vaccine efficacy values to provide some guidance about mitigation as waning efficacy occurs and new variants emerge. For example, the existing Pfizer vaccine was only 33% effective at reducing new infections against the Omicron variant in late 2021 (Scobie 2021; Figure S1, available online in Supporting Information). Based on  $V_E$  and community COVID-19 prevalence, the probability that a vaccinated worker is positive and shedding virus is:

$$p_{vaccine}^+ = \psi - (V_E \times \psi).$$

If a crew member is unvaccinated and does not take a test, the probability that they are positive and shedding virus can be estimated by the local prevalence,  $\psi$ , or by some other method that accounts for the crew member's risk behavior (e.g., https://www.microcovid.org/).

#### Bat encounter types and exposure probabilities

To calculate the number of bats handled (*H*), encountered in an enclosed space (*E*), or in proximity to workers in an unenclosed space (*P*), we multiplied the total number of bats encountered in a typical season of work by the percentage of each bat encounter type (Table 1). We used the same encounter estimates reported in Runge et al. (2020), based on reporting data from Colorado Parks and Wildlife, Connecticut Department of Energy and Environmental Protection, Kentucky Department of Fish and Wildlife, Virginia Department of Game and Inland Fisheries, Wisconsin Department of Natural Resources, USDA Forest Service, National Park Service, U.S. Geological Survey, and the White-nose Syndrome surveillance program. For RSM activities, most bat interactions involve handling (45.8%), followed by activities in proximity to bats (42.7%), and sharing an enclosed space with bats (11.5%). For WR, all documented human bat interactions result from handling (100%). For WC, most human-bat interactions occur when a practitioner comes within 1.83 m (6 feet) of a bat (77.1%) but does not handle the bat; the other 22.9% of interactions involve bat handling (Table 1).

For each human-bat activity and encounter type, Runge et al. (2020) used formal expert judgment protocols, notably the IDEA (Investigate, Discuss, Estimate, Aggregate) protocol (Hanea et al. 2017) and the 4-point elicitation method (Speirs-Bridge et al. 2010), to estimate unique probabilities of exposure and an associated measure of uncertainty (i.e.,  $\beta$  parameters in infection risk model equations). The 4-point elicitation method provided a point estimate and a measure of within-expert uncertainty by eliciting each expert's lowest, highest, and best estimates of

**TABLE 1** Fraction of bats encountered through each of 3 encounter types for each of 3 activities. The 3 encounter types are: handling (Handling); encounter within 1.83 m in an enclosed space (Enclosed); and proximity within 1.83 m in an unenclosed space (Proximity). The data were gathered from the following agencies: Colorado Parks and Wildlife, Connecticut Department of Energy and Environmental Protection, Kentucky Department of Fish and Wildlife Resources, New York State Department of Environmental Conservation, Oregon Department of Fish and Wildlife, Virginia Department of Game and Inland Fisheries, Wisconsin Department of Natural Resources, Forest Service, National Park Service, U.S. Geological Survey, and the White-nose Syndrome surveillance program (Runge et al. 2020).

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

model parameters as well as an estimate of confidence that their reported values included the true value. The expert panel included 13 individuals with diverse professional experience and specializations in wildlife epidemiology, virology, bat physiology, and bat ecology (Runge et al. 2020). Two rounds of elicitation were held, and group meetings in-between rounds were used to clarify questions and responses, with the aim of reducing sources of expert bias. To estimate an aggregate expert distribution from individual responses, the parameters that best fit probability distributions to the elicited quantiles from each expert independently were identified. Then parameters for an aggregate distribution were estimated by averaging the independent probability density functions (PDFs) across all experts and finding parameters for a fitted aggregate distribution that minimized the Kullback-Leibler distance (Kullback and Leibler 1951) between the average PDF and the fitted PDF.

For RSM activities, experts estimated a median of 49.7 bats (80% confidence interval (CI) = 15.3, 84.3) exposed out of 100 encountered during handling, a median of 19.4 bats (80% CI = 2.2, 72.4) exposed out of 100 encountered when in enclosed space within 1.83 m of a SARS-CoV-2 positive scientist, and a median of 6.4 bats (80% CI = 0.6, 43.8) exposed out of 100 within 1.83 m of a SARS-CoV-2 positive scientist in an unenclosed space. For WR activities, experts estimated a median of 70.4 bats (80% CI = 24.4, 94.6) exposed out of 100 during handling and a median of 24.3 bats (80% CI = 2.8, 78.4) exposed out of 100 when within 1.83 m of a SARS-CoV-2 positive wildlife rehabilitator. For WC activities, experts estimated a median of 27.7 bats (80% CI = 3.7, 79.2) exposed out of 100 during handling and 9.6 bats (80% CI = 1.0, 53.9) exposed out of 100 when within 1.83 m of a SARS-CoV-2 positive WC operator.

In addition to COVID-19 testing for risk mitigation, agencies can issue guidelines for properly fitted PPE use during human-bat interactions. In Runge et al. (2020), the effectiveness of N95 respirators for mitigating the risk of SARS-CoV-2 exposure during RSM, WR, and WC activities was evaluated. Following that publication, additional information identified aerosolized virus as the primary pathway of human-to-human disease exposure (Meyerowitz et al. 2021); thus, we can evaluate the ability of other face coverings to reduce viral exposure of bats if we can assume that exposure probabilities from Runge et al. (2020) are reduced by reported filtration efficiencies of other PPE types. Common PPE types include: N95 respirators (percent filtration efficiency (FE) mean  $\pm$  SD = 99.4  $\pm$  0.2; 3 M model 1870), surgical masks (FE = 89.5  $\pm$  2.7), cloth masks (FE = 50.9  $\pm$  16.8), and face shields (FE = 23  $\pm$  3.3; Davies et al. 2013, Lindsley et al. 2014, Long et al. 2020).

## Probability of susceptibility

We used probability of bat susceptibility ( $\sigma_{sp}$ ) estimates that were derived from expert judgment using the same structured protocols described above. In the Cook et al. (2021) application, the expert panel included a diverse

group of 12 professionals, 4 of whom participated in the Runge et al. (2020) study. Similar to Runge et al. (2020), 2 rounds of elicitation were held, and the probability of susceptibility for LBB was estimated using fitted aggregate group distributions based on the 12 expert responses.

The probability-of-susceptibility estimates, probability of infectious crew members, and effectiveness of PPE were then used to estimate the number of LBB that could be infected out of 1000 encountered during RSM, WC, and WR activities. For all comparisons, unless otherwise specified, we assumed that the local COVID-19 prevalence was 0.05. Each infection risk model was simulated 100,000 times to explore uncertainty in the parameters. All analyses were performed in Program R (R Core Team 2018).

# RESULTS

# Probability of susceptibility

Conditional on a sufficient dose of SARS-CoV-2 for individual bat infection, the expert panel from Runge et al. (2020) estimated that the median probability of susceptibility for LBB was 0.44 (80% prediction interval (PI) = 0.08, 0.88). Following the accumulation of new information, a follow-up expert elicitation estimated that the median probability of susceptibility of susceptibility was 89% lower and had less uncertainty (Cook et al. 2021; Figure 2; median probability of susceptibility: 0.05; 80% PI = 0.003, 0.37). The updated estimate was informed, in part, by new information, including human and bat ACE2 receptor homology (Damas et al. 2020), and the availability of lab-based challenge studies (Hall et al. 2020).

# **Baseline risk**

We reanalyzed the infection risk models described in Runge et al. (2020) using updated estimates of the probability of susceptibility for LBB reported in Cook et al. (2021). We found an 87–88% decrease in the median number of bats



**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).



**FIGURE 3** Number of bats per 1,000 exposed to and infected by SARS-CoV-2 by the three transmission pathways. RSM = research, survey, monitoring, or management activities; WR= wildlife rehabilitation; WC = wildlife control operations. Boxplot whiskers represent 99% prediction interval. For comparisons, we used the same assumed ratio of encounter modes (handling, enclosure, and proximity) and probability of worker shedding SARS-CoV-2 (median: 0.057; 80% CI: 0.022, 0.112) from Runge et al. (2020). (A) Results reproduced based on expert-elicited data on probability of bat susceptibility from Runge et al. (2020) assessment. (B) Results based on parameter values from Cook et al. (2021) assessment.

estimated to be infected per 1000 encountered when compared against the earlier results. For RSM activities, the median number of bats infected per 1000 was estimated to be 6.96 in the Runge et al. (2020) assessment (Figure 3A; 80% CI = 1.85, 19.41). Using updated probability of susceptibility estimates, we found that the median number of bats estimated to be infected by SARS-CoV-2 was less than one individual per 1000, which is 88% lower than the initial estimate (Figure 3B; median: 0.83, 80% CI = 0.07, 7.82). For WR encounters, the median number of bats infected per 1000 was reduced from 13.03 (Figure 3A; 80% CI = 3.54, 36.14) to 1.56–a similar 88% decrease in the median value (Figure 3B; 80% CI = 0.12, 14.71). For WC encounters, the median number of bats infected per 1,000 was reduced from 3.72 (Figure 3A; 80% CI = 0.84, 14.43) to 0.47–an 87% decrease in the median value (Figure 3B; 80% CI = 0.03, 4.79).

We also analyzed the baseline bat infection risk across 3 different levels of COVID-19 prevalence (Figure S2, available online in Supporting Information). For RSM activities, the median number of bats infected per 1000 encountered fell from a median of 0.83 (80% CI: 0.07, 7.82), when COVID-19 prevalence was 0.05, to a median of 0.15 (80% CI: 0.01, 1.29) and 0.015 (80% CI: 0.001, 0.129), when COVID-19 prevalence was 0.01 and 0.001, respectively. For WR activities, the median number of bats infected per 1,000 fell from a median of 1.56 (80% CI: 0.12, 14.71), when COVID-19 prevalence was 0.05, to a median of 0.27 (80% CI: 0.02–2.34) and 0.027 (80% CI: 0.002, 0.23), when COVID-19 prevalence was 0.01 and 0.001, respectively. For WC activities, the median number of bats infected per 1,000 fell from a median of 0.47 (80% CI: 0.03, 4.79), when COVID-19 prevalence was 0.05, to a median of 0.08 (80% CI: 0.03, 4.79), when COVID-19 prevalence was 0.01 and 0.001, respectively. For WC activities, the median of 0.88 (80% CI: 0.000, 0.28), when COVID-19 prevalence was 0.05, to a median of 0.47 (80% CI: 0.03, 4.79), when COVID-19 prevalence was 0.05, to a median of 0.08 (80% CI: 0.005, 0.08), when COVID-19 prevalence was 0.01 and 0.001, respectively.

## **Risk mitigation**

We used the updated parameter estimates to evaluate the effectiveness of pre-survey COVID-19 testing and vaccination, as well as additional face coverings for reducing baseline risk (Figures 4 and 5).



**FIGURE 4** 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 and mRNA vaccination (vax = vaccination). RSM = research, survey, monitoring, or 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.

We estimated that the median number of SARS-CoV-2 infected bats out of 1,000 encountered decreased by 65–67% across all 3 encounter types (i.e., RSM, WR, and WC) from a negative test of field crew 3 days prior to bat handling. Further, our updated estimate was reduced by 88–89% when compared against the initial Runge et al. (2020) results (Figure 4). For vaccination, the median estimate was reduced by 86–88% across encounter types. When COVID-19 testing and vaccination were used in combination, risks were reduced by 98–99% (Figure 4).

We found that N95 respirators reduced the median estimates of infection by 95–96% for all 3 encounter types when compared against median values with updated parameter estimates and without enhanced PPE (Figure 5A, B, C; overall reduction of 99% from Runge et al. 2020). For surgical masks, we found an 89% reduction in the median estimate of infection for all 3 encounter types (i.e., RSM, WR, and WC work; Figure 5A, B, C), when compared against median values with updated parameter estimates and without enhanced PPE. For cloth masks, we found a reduced median estimate of infection of 54–55% for all 3 encounter types (Figure 5A, B, C), when compared against median values with updated parameter estimates and without enhanced PPE. Finally, for face shields, we found a reduced median estimate of infection of 22–24% for all 3 encounter types when compared against median values with updated parameter estimates and without enhanced PPE.

# DISCUSSION

The existing decision framework developed in Runge et al. (2020) allowed for a rapid re-evaluation of human-to-bat SARS-CoV-2 transmission risk during summer fieldwork based on new knowledge included in Cook et al. (2021), expert judgment, and other empirical studies. We found that new knowledge substantially reduced uncertainty, lowered risk estimates, and provided additional management alternatives that may be important to preventing SARS-CoV-2 infection in bats during RSM, WR, and WC activities. More broadly, we found that decision analysis



**FIGURE 5** Number of bats per 1,000 exposed to and infected by SARS-CoV-2 by the three transmission pathways. RSM = research, survey, monitoring, or 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.

coupled with expert judgment provided substantial benefits to decision makers across the 3 studies (Runge et al. 2020, Cook et al. 2021, this study); we expect that these benefits transcend SARS-CoV-2 to other wildlife disease systems. Decision analysis helped to identify the fundamental management objectives, specify alternatives, direct the development of quantitative infection risk models, and ultimately, create a risk assessment framework that remained useful over time and as our knowledge of the novel pathogen system improved. Formal expert judgment allowed us to estimate parameters with the available information in a timely manner, without having to initiate and wait for the results of new empirical studies.

We found that the median numbers of LBB potentially infected during summer RSM, WR, and WC activities were reduced substantially from those reported in the initial Runge et al. (2020) assessment, in part because an expanded range of management alternatives were available to further reduce these risks. By expanding the range of alternatives for preventing transmission, we provide decision makers with additional options (and estimates of their effect on the number of infected bats) that may address concerns for human-bat interactions. For example, if the baseline risk of an activity exceeds an agency's tolerance for risk, they may choose to require COVID-19 testing or vaccination prior to planned human-bat encounters, or the use of enhanced PPE during encounters. Although RT-PCR COVID-19 testing may be difficult to implement in certain situations, especially for WR and WC activities that can arise spontaneously rather than from advanced planning, vaccines can be used prophylactically. Other, more rapid, COVID-19 tests are available and have practical application to spontaneous activities. We did not

evaluate them here because they are less reliable (i.e., rapid antigen tests have higher rates of false negative results; Jegerlehner et al. 2021) and less predictable (i.e., there is greater potential for user error because they are often administered by untrained individuals) when compared to RT-PCR testing. Finally, it is important to note that risk tolerance may differ among agencies, and thus the response to the same risk may differ markedly in the decisions made (Sells et al. 2016).

Across the 3 risk assessments (Runge et al. 2020, Cook et al. 2021, this study), expert judgment was critical to our ability to estimate SARS-CoV-2 risk to bats. At the time of Runge et al. (2020) and Cook et al. (2021), there were no data from empirical studies available to directly inform LBB susceptibility to SARS-CoV-2 infection. Instead, structured protocols were implemented that derived unknown parameter estimates using leading experts in relevant fields of study. Expert judgment has gained credibility across a diversity of decision-making applications because it provides a viable alternative when empirical data are not yet available for generating parameter estimates (Tyshenko et al. 2016, Bianchini et al. 2020), quantifying uncertainty (McBride et al. 2012, Conroy and Peterson 2013) and controlling for sources of bias (McBride et al. 2012). We found expert elicitation to be particularly powerful because it allowed us to rapidly integrate the best available science and knowledge for guidance to managers dealing with uncertain but immediate risks to some NA bats.

Throughout 2021, widespread vaccination efforts have reduced the risk of SARS-CoV-2 exposure to bats. Individual workers who are vaccinated prior to human-bat encounters can directly lower the likelihood that they are infected and shedding SARS-CoV-2 at the time of those encounters; however, the period of immunity for those vaccinated and the efficacy of existing vaccines against newly emerging viral strains remains uncertain. There is now mounting evidence that vaccine efficacy wanes over time and that vaccines formulated against earlier strains may not be as effective at preventing infection with new strains (Scobie 2021, Nordstrom et al. 2022). As more information becomes available on the duration and level of protection provided by vaccination and the role of new strains with immune-escape properties, the risk assessments in this paper can be reevaluated.

Although decision framing, expert judgment, and the development of a quantitative risk model assisted in the production of decision-relevant science, the timely release of our results to support decision-making remained a challenge. Across the first 2 studies, the production of science happened over the course of several weeks, including several rounds of agency consultation and the development of risk models. For information sharing, we provided the results to decision makers in a timely fashion through briefings after we had peer review and agency clearance, but before the results were published. The agencies, however, were interested in timely publication so they could cite the research when communicating their decisions to the public. In total, the documentation, external peer-review, and publication process added an additional 5.5 weeks for Runge et al. (2020) and 11.5 weeks for Cook et al. (2021). Although these timelines are typical and necessary for rigorous peer review, shorter timelines for studies on emergent wildlife disease risks could be helpful because the decisions they are intended to inform may be necessary before completion of a standard peer-review and publication process. It is not our intention to criticize any journal, reviewers, or peer-review process, but we recognize the importance of decision-relevant science to inform urgent agency decisions.

There are likely many options to improve the timely delivery of science moving forward, and we provide suggestions that may be useful. First, journals may consider creating alternate production tracks to expedite peerreview and publication. Alternative options for distribution, such as preprint servers (like bioRxiv and medRxiv) have already become avenues for timely release of information during the COVID-19 pandemic; however, these avenues do not address the critical role that peer-review plays in the production of reliable science. Second, for agencies that frequently make urgent decisions and that currently rely only on published results to support those decisions, it may be beneficial to use external science review boards that can objectively evaluate the quality of unpublished findings. Lastly, risk assessment teams could establish and rely on pre-approved methods to produce rapid assessments of wildlife disease risks within hours or days of an identified novel hazard. Although these assessments may be based on preliminary results and generalized methodology that is subject to refinement as knowledge improves, they can be effective as a bridge to more rigorous assessments that include agency consultation, quantitative modeling, and the evaluation of specific management alternatives. Nevertheless, we hope that our risk assessments may serve as a model to assess threats that SARS-CoV-2 continues to present to wildlife, and that a larger discussion be stimulated to identify the best approaches to deliver decision-relevant science for emerging wildlife diseases on timescales that matter.

Moving forward, it will be possible to update future SARS-CoV-2 risk assessments as knowledge of critical uncertainties improve and we learn more about the susceptibility of bats and other wildlife to novel strains. At this time, SARS-CoV-2 has been detected in companion, zoo, and wild animals. Of particular concern are transmission events between humans and captive mink (Oude Munnink et al. 2021), the detection of widespread SARS-CoV-2 antibodies in white-tailed deer (Kuchipudi et al. 2022), and continued expansion in the range of hosts. The long-term implications of SARS-CoV-2 in farmed or wild animals remain unclear, as does their ability to serve as reservoir hosts. Viruses rapidly mutate, recombine, and evolve in host species, as evident in the emergence of the highly transmissible Omicron variant in humans. How novel strains affect the susceptibility of wildlife to the pathogen is not yet understood. Broadly-applicable risk mitigation strategies informed by One Health could be useful across a diversity of human-animal interactions to reduce the potential for future zoonotic transmission. Decision analysis is also useful to guide more targeted risk assessments and inform agency decisions about human-wildlife interactions as pathogens, and our understanding of them, evolves.

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#### CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

#### DATA AVAILABILITY STATEMENT

The data underlying this article will be shared on reason-able request to the corresponding author.

#### ETHICS STATEMENT

All data used in these analyses were provided as electronic records and no vertebrate species were contacted or handled as a direct result of this study.

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