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Evaluating the effect of expert elicitation techniques on population status assessment in the face of large uncertainty

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ABSTRACT

Population projection models are important tools for conservation and management. They are often used for population status assessments, for threat analyses, and to predict the consequences of conservation actions. Although conservation decisions should be informed by science, critical decisions are often made with very little information to support decision-making. Conversely, postponing decisions until better information is available may reduce the benefit of a conservation decision. When empirical data are limited or lacking, expert elicitation can be used to supplement existing data and inform model parameter estimates. The use of rigorous techniques for expert elicitation that account for uncertainty can improve the quality of the expert elicited values and therefore the accuracy of the projection models. One recurring challenge for summarizing expert elicited values is how to aggregate them. Here, we illustrate a process for population status assessment using a combination of expert elicitation and data from the ecological literature. We discuss the importance of considering various aggregation techniques, and illustrate this process using matrix population models for the wood turtle (*Glyptemys insculpta*) to assist U.S. Fish and Wildlife Service decision-makers with their Species Status Assessment. We compare estimates of population growth using data from the ecological literature and four alternative aggregation techniques for the expert-elicited values. The estimate of population growth rate based on estimates from the literature (λ_{mean} = 0.952, 95% CI: 0.87–1.01) could not be used to unequivocally reject the hypotheses of a rapidly declining population nor the hypothesis of a stable, or even slightly growing population, whereas our results for the expert-elicited estimates supported the hypothesis that the wood turtle population will decline over time. Our results showed that the aggregation techniques used had an impact on model estimates, suggesting that the choice of techniques should be carefully considered. We discuss the benefits and limitations associated with each method and their relevance to the population status assessment. We note a difference in the temporal scope or inference between the literature-based estimates that provided insights about historical changes, whereas the expert-based estimates were forward looking. Therefore, conducting an expert-elicitation in addition to using parameter estimates from the literature improved our understanding of our species of interest.

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1. Introduction

Managers are often tasked with making consequential decisions when little information is available (Nichols, 2019; Robinson et al., 2016; Williams, 1997, 2001). Therefore, an important role of science in the conservation decision-making process is the development of models to forecast future conditions while accounting for various sources of uncertainty (Williams et al., 2002). Conservation decisions must be based on the best available data; though, it is common that important decisions have to be made even when the best available data is very sparse (Regan et al., 2005). On the other hand, postponing decisions until better information becomes available may reduce the ability to make a management decision or the potential benefit of a conservation decision (Drechsler et al., 2011; Grant et al., 2013).

When empirical data are not available, the best practices of expert judgement and elicitation can be used to inform model parameter estimates. Expert judgement has a long history of use in many disciplines, such as public health, engineering, and business and has seen increasing use in natural resource management in recent years (Colson and Cooke, 2018; Hora et al., 2013; Lyon et al., 2015; Morgan, 2014; Sutherland and Burgman, 2015). Modelled outputs from expert elicitation have several benefits for natural resource management and conservation: (1) they can serve as informed placeholders for empirical data, enabling managers to make decisions without delay; (2) they may provide a basis for informing better prioritization of monitoring programs; (3) they may allow experts to use empirically estimated vital rates and life history knowledge for a species to forecast demographic responses to future conditions; and (4) they are well suited for incorporating key sources of uncertainty, which can be propagated in empirical projection models for forecasts (Canessa et al., 2016; Converse et al., 2013; Cummings et al., 2020; Johnson et al., 2017; Martin et al., 2017; McBride et al., 2012; Runge et al., 2011). Additionally, as a part of this process, expert elicited estimates are updated as more empirical information about a system becomes available, which increase knowledge about the system and provides more reliable model outputs.

Despite the applications, expert elicitation is still affected by the same kinds of structural, analytic and interpretive biases that are common to the scientific process. For example, the rigor used in elicitation of expert judgment and the aggregation of elicited estimates can influence the performance of the prediction models, and thus the basis for any conservation decision (Hanea et al., 2017; Runge et al., 2011). Ideally, synthesis of expert knowledge should account for variation within and among experts (Runge et al., 2011). To account for this, common aggregation methods include mean and median-based approaches (Colson and Cooke, 2018). Hora et al. (2013) showed that the *median-based approach* performs well when experts are well-calibrated (i.e., they express the true probability with appropriate confidence) and independent (i.e., their responses are not influenced by the responses of other experts), whereas the *mean-based approaches* are better when those assumptions are relaxed. More recently, aggregation methods that explicitly account for within and among expert variations have also been implemented (e.g., Johnson et al., 2017; Martin et al., 2017; Runge et al., 2017), but some of these methods may result in multimodal probability distributions. Each of these approaches have their strengths and limitations that warrant examination in this particular modeling context; yet few studies have examined the sensitivity of population models to these alternative aggregation techniques. Therefore, the influence of aggregation techniques on population models remains poorly known.

Formal species status assessments represent a case in which important conservation policy decisions must be made in the face of sparse data and large uncertainty about the future. These population assessments satisfy the information needs to make decisions under U.S. laws such as the Endangered Species Act of 1973 (ESA; 16 USC. §1531 et seq., as amended) and the Marine Mammal Protection Act of 1972 (MMPA; 16 USC. §1361 et seq., as amended). The general goal of these laws is to protect and conserve species and their habitats. More recently, the U.S. Fish and Wildlife Service (USFWS) has developed a Species Status Assessment (SSA) framework to provide the scientific foundation to inform ESA decisions, such as candidate assessment, listing, consultations, and recovery of species (U.S. Fish and Wildlife Service, 2016). As part of a SSA, there is a scientific review to evaluate its status in regards to representation, redundancy, and resiliency through analysis of best available data and associated models (Cummings et al., 2020).

Population projection models are useful quantitative tools to assess the status of populations, quantify the impacts of identified threats, and evaluate the potential results of management actions (Beissinger and McCullough, 2002; Caswell, 2006; Martin et al., 2008; Morris and Doak, 2002). Several population projection models have used a combination of empirically-based estimates and expert elicited estimates in their models to assess the status of threatened populations (e.g., Runge et al., 2011). As additional information is accumulated through research and monitoring programs, the expert-elicited estimates can be replaced with empirical information. Importantly, the population model can be used to help prioritize scientific investments by identifying the most important sources of uncertainty for the purpose of better management (Hostetler et al., 2021; McGowan et al., 2011; Runge et al., 2007, 2011).

Here, we develop a matrix population model for the wood turtle (*Glyptemys insculpta*) to assist USFWS decision-makers with this species' SSA process. We obtained demographic parameter estimates from the literature, and via a formal expert elicitation approach. We compare estimates using data from the ecological literature and three alternative aggregation techniques for the expert elicited values. We then discuss the benefits and limitations of using each of these data sources and aggregation techniques for synthesizing information for the population assessment.

2. Methods

2.1. Case study species

The wood turtle is a long-lived freshwater turtle species endemic to North America. Populations are found from Virginia, United States to Nova Scotia, Canada, and from the east coast of the United States west to Minnesota (Ernst and Lovich, 2009; Powell et al., 2016). Wood turtles are semi-aquatic and associated with river, stream, and riparian habitats throughout their range, though suitable habitat for this species is expected to decrease by at least a third over the next 50 years due to changes linked to climate patterns (Mothes et al., 2020). Female wood turtles lay one clutch annually, nesting in late spring to early summer (Harding and Bloomer, 1979). In freshwater turtles, survival is typically size-related as smaller individuals are more susceptible to predators and winter mortality, and is lowest in the first year but increases as they grow toward maturity (Bodie and Semlitsch, 2000; Haskell et al., 1996), after which it remains constant (Jones, 2009).

The wood turtle is considered Endangered according to the International Union for the Conservation of Nature (IUCN) Red List assessment (van Dijk and Harding, 2011). At the state and provincial level, the wood turtle is a species of special concern, vulnerable, threatened, or endangered across its range. In 2012, the USFWS received a petition to list the wood turtle as either Threatened or Endangered and designate critical habitat pursuant to the ESA (Adkins Giese et al., 2012). Consequently, the USFWS must review the species' status to determine if listing the species is warranted.

2.2. Parameter estimates from the literature

We conducted a literature review using the key words "wood turtle", "*Glyptemys insculpta*", and "*Clemmys insculpta*" to find all published articles on this species through Google Scholar, as well as reviewed U.S. government reports, and unpublished theses up until 2018 (see full list in Supplementary material). From these articles, we extracted any

Table 1
Population parameters and their definition.

Population Parameter	Definition
Clutch size	Number of eggs laid
Nest survival[a]	Probability of the nest surviving (entire nest)
Survival of eggs	Probability of each individual egg surviving to hatch
Survival of hatchlings	Probability of each hatchling survival to year one
Survival of juveniles	Probability of juvenile turtles surviving to the next year
Survival of juveniles (age 1–2)[a]	
Survival of juveniles (age 2–3)[a]	
Survival of juveniles (age 3–6)[a]	
Survival of juveniles (age 6–12)[a]	
Age of first reproduction	Age at which the turtle first developed eggs
Proportion of adults that reproduce	Proportion of adult turtles which reproduced each year
Survival of adults	Probability of adult turtles surviving to the next year

[a] Parameters elicited from experts but not available in the literature.

estimates presented, either measured directly in the field or from model-based approaches, of the population parameters of interest (Table 1). Survival of juveniles was estimated for the age class as a whole and not broken down into more specific ages, as this level of detail was not available from the literature.

2.3. Parameter estimates from expert elicitation

We used a modified version of the Investigate Discuss Estimate Aggregate (IDEA) protocol for the expert elicitation (Hanea et al., 2017): Specifically, (1) we investigated the available information on wood turtles; (2) we discussed the information and potential mechanisms related to the population dynamics of wood turtles; (3) we elicited the parameter estimates; and (4) we aggregated the estimates from the experts (Hanea et al., 2017; Martin et al., 2017). We went through these four steps during a full-day workshop in Berkeley Springs, West Virginia on 6 November with nine participating experts from several states throughout the wood turtle range. The in-person workshop was preceded by a video conference during which we introduced the participants to a prototype population model for the wood turtle and discussed the expert elicitation process. During this videoconference, we provided an overview on the importance of cognitive biases, such as overconfidence and anchoring (Sutherland and Burgman, 2015). We also conducted a calibration training study, in which we asked the participants to provide their "low", "high" and "best" values for a fixed confidence level of 95% (i.e., a three-point-elicitation), for three "seed variables" (i.e., quantities that are known to the analyst, but unlikely to be known by the expert): seed variable (1) - carapace length (cm) of adult female Diamondback Terrapins (*Malaclemys terrapin*); seed variable (2) - carapace length (cm) of adult male Diamondback Terrapins; seed variable (3) - clutch size of Diamondback Terrapins. The purpose of this calibration training study was to help the experts assess their level of overconfidence and to become familiar with the expert elicitation process. Although the participants worked on these estimates on their own time, we asked them not to use any aid for the calibration study. At the beginning of the workshop, we showed the results of the calibration study.

During the workshop we discussed each demographic rate for wood turtles (i.e., the model parameters; Table 1) in detail. The confidence level for the wood turtle demographic parameters was set at 95%; that is, we asked the participants to be 95% confident that the "true" value was within the "low" and "high" values that they provided to us. The wood turtle has a large range in North America and likely has differences in population parameters across the latitudinal gradient. To account for this, the participants agreed to express their parameter values for an average population in the middle of the eastern portion of the range as the population of interest (Fig. 1; Jones and Willey, 2021).

After the workshop we organized two additional rounds of elicitations, before each new elicitation we provided the participants with a summary of the aggregated results and discussed these results to reduce the risk of misunderstanding about how the parameters were defined (linguistic uncertainty). We emphasized that the purpose of the additional rounds of elicitation was not to reach consensus, but instead to make sure that the group had reached a common understanding of the parameter definitions. The participants were allowed to use any sources of information available to them including estimates compiled from the literature and provided to them in the first step of the IDEA protocol. During the group discussions we encouraged experts to discuss

Table 2
Mean and variance for each parameter from the literature review or the expert elicitation for an average, good, or bad year, including the symbol used for each parameter.

	Symbol	Literature	Expert Average Year	Expert Good Year	Expert Bad Year
Clutch size	c	9.048 (1.215)	9.667 (2.5)	10.778 (5.194)	8.222 (1.944)
Age of first reproduction	age	15.07 (3.838)	13.778 (1.444)	13.333 (2.250)	14.556 (1.278)
Proportion of adults that reproduce	r	0.653 (0.049)	0.706 (0.012)	0.844 (0.015)	0.500 (0.011)
Nest survival	$nest$	–	0.306 (0.017)	0.436 (0.020)	0.219 (0.052)
Survival of eggs	se	0.710 (0.026)	0.718 (0.010)	0.843 (0.014)	0.578 (0.011)
Survival of hatchlings (0–1)	sh	0.110[a]	0.199 (0.010)	0.378 (0.025)	0.114 (0.009)
Survival of juveniles (1–12)	sj	0.820 (0.0002)	0.642 (0.017)	0.748 (0.014)	0.483 (0.022)
Survival of age 1–2	sj_1	–	0.319 (0.009)	0.450 (0.004)	0.233 (0.009)
Survival of age 2–3	sj_2	–	0.461 (0.011)	0.550 (0.003)	0.364 (0.009)
Survival of age 3–6	sj_3	–	0.633 (0.009)	0.719 (0.006)	0.521 (0.012)
Survival of age 6–12	sj_6	–	0.824 (0.001)	0.891 (0.001)	0.706 (0.004)
Survival of adults (12+)	sa	0.908 (0.002)	0.907 (0.004)	0.931 (0.008)	0.750 (0.022)

[a] From the literature, there is only one estimate for survival of hatchlings.

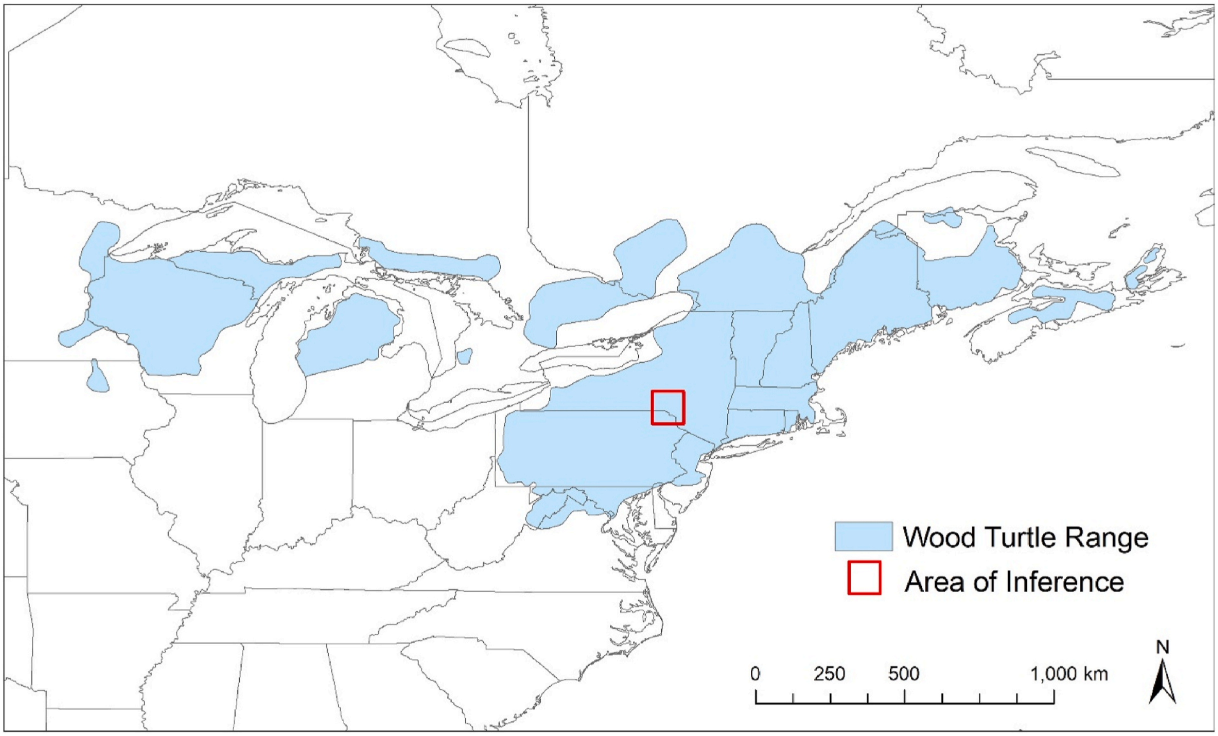

Fig. 1. Range of the Wood Turtle in North America with a red square indicating the approximate area that the experts used when providing parameter estimates for the population model. (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

limitations of the studies available in the literature and to discuss their own studies and observations. Experts were encouraged to think about vital rates with a time horizon of 20 years into the future. In order to account for environmental stochasticity, we asked the participants to provide estimates for three categories of years "good conditions," "average conditions," and "bad conditions," with the assumption that each type of year had an equal probability of occurrence, or independent and identically distributed (iid) sequences (Caswell, 2006).

2.4. Matrix population projection model

We used matrix models to compute the population growth rates using parameter estimates from the literature and the expert elicitation process (Moore et al., 2021). We used these matrix models to estimate both deterministic (λ) and stochastic population growth rate (λ_s). Stochastic population growth rates were used to model the environmental variation (over a 20-year period). We estimated population growth rates based on the average demographic values from the literature and experts as well as using distributions based on all demographic values from the sources, accounting for parameter uncertainty. In addition, we ran a sensitivity analysis to understand the effect of each parameter on the population growth rate.

2.4.1. Input parameter estimates

First, we calculated the mean and variance for each input population parameter based on values from the literature, as well as estimates from the experts for good, average, and bad years. Because we had multiple estimates for each population parameter, either multiple sources from the literature review or estimates from each expert, we also fit a distribution to the estimates for each parameter, which allowed us to consider parameter uncertainty in our models. In all cases, we fit a beta distribution to all survival parameters and the annual proportion of reproducing adults, and a double Poisson distribution to all discrete count parameters (i.e., clutch size and age of first reproduction) because the variance was lower than the mean for the latter. Distributions were fit using the *rriskDistributions* package (Belgorodski et al., 2017), the *gamlss* package (Rigby and Stasinopoulos, 2005), and the *gamlss. dist* package (Stasinopoulos and Rigby, 2020) in the statistical software R (R Development Core Team, 2019).

2.4.2. Aggregation methods

We used five different aggregation methods for compiling our estimates before fitting the aforementioned distributions: one method for the literature values and four methods for the expert values. For the literature values, we used the method of moments to fit distributions to the parameters using the mean and variance of each set of estimates. Because we had only one estimate for survival of hatchlings, we fit the distribution to the calculated quantiles by assuming a 10% coefficient of variation (CV).

For the expert values, we elicited estimates for each parameter plus 95% confidence intervals. We aggregated these estimates in four ways and fit a distribution for each parameter for good, average, and bad years.

(1) We used an aggregation of expert assessments that took the mean of the elicited quantiles: the *mean-based approach (A1)*. We fit distributions to the 95% quantiles using the average estimates from the experts. We took the average low estimate (2.5% quantile), median estimate (50% quantile), and high estimate (97.5% quantile) for each parameter.
(2) For the second aggregation method (hereafter, *A2*), we used the *median-based approach.* This is similar to *A1*, but using the median of the elicited quantiles instead of the mean. Hora et al. (2013) showed that the *median-based approach* performs well when experts are well-calibrated and independent, but that the *mean-based approaches* are better when those assumptions are relaxed.
(3) For the third aggregation method (hereafter, *A3*), we followed aspects of Johnson et al. (2017) to fit distributions for each expert, and then drew 10,000 samples for each parameter. The samples for each parameter were pooled across experts to

produce a single distribution for each parameter. We assigned equal weights to all experts.

(4) For the fourth aggregation method (hereafter, *A4*), we used the steps described for method *A3*, but, then we used the quantiles (2.5%, 50%, 97.5%) of this distribution to fit a unimodal distribution to avoid multi-modal distributions.

Probability distribution functions and summary statistics for each distribution based on the different aggregation methods are included in the supplementary material.

2.4.3. Matrix model formulation

We constructed a post-breeding age-structured matrix model based on the life history of the wood turtle (Fig. 2). First, we created four matrices based on the average parameter estimates from the literature and the experts for an average, good, and bad year. Next, to incorporate parameter uncertainty, we simulated 50,000 matrices pulling values independently from the distribution for each parameter (i.e., each simulation we pull one value from the distribution for each parameter and create a matrix output). We simulated a set of matrices for each of the five aggregation methods described above, one for the literature and four for the expert values. For the expert values, we simulated a set of matrices using a single juvenile survival value and a set of matrices using four juvenile survival categories. We also allowed age of first reproduction to vary based on the fitted distribution, or we fixed it at 14 years of age, which was the average age of first reproduction based on the estimates from the experts for an average year. This resulted in a total of five simulated sets of matrices for each of the four aggregations based on expert-elicited values plus one set of matrices for the literature values.

2.4.4. Population growth rate

We calculated the deterministic population growth rate (λ) as the dominant eigenvalue of the matrix model. We present the mean of the λ values across all 50,000 matrices for each set. For the expert values, we also calculated the stochastic population growth rate (λ_s). Stochastic population growth rate considers the parameter estimates for good, average, and bad years, assuming each type of year has a 1/3 chance of happening each year (Caswell, 2006). We calculated stochastic population growth rate using all aggregation methods for the expert values with one juvenile survival class or multiple juvenile survival classes with the age of first reproduction fixed at the average value. We estimated stochastic population growth rate using Tuljapukar's approximation (Morris and Doak, 2002; Tuljapurkar and Orzack, 1980). All population growth rates were calculated using the *popbio* package in R (Stubben and Milligan, 2007).

2.4.5. Sensitivity analysis

Finally, we conducted a sensitivity analysis to test the effect of each survival parameter on the deterministic population growth rate (Caswell, 2006). Using the average values from the experts for an average year, we created a matrix assuming a fixed age of first reproduction of 14 years. We then allowed hatchling survival, juvenile survival, and adult survival to vary from 0 to 1, and examined the effect of the change in the parameter on the estimated population growth rate.

3. Results

Overall, we found that empirical data in the literature varied markedly for some parameters from expert-elicited values (Table 2; Supplementary Material). In some cases (i.e., age of first reproduction and survival of juveniles), estimates from the literature were higher than all values from the experts. However, for other parameters (i.e., survival of hatchlings), estimates from the literature were lower than all estimates from the experts even from a bad year. Some estimates (i.e., survival of adults and survival of eggs) were very similar between the literature and the expert estimates for an average year. It is worth noting there is considerable variation among different studies in the literature, and among experts, for most of the parameters, noted by the large variances for some parameters.

Using the average values obtained from the literature and the experts for average, good, and bad years, the mean finite growth rate varied between $\lambda = 0.750$ and $\lambda = 0.970$ (Table 3). This range of estimates indicates population decline, between 3 and 25% per year, and the magnitude of the decline relates to whether the year is good, average, or bad. The estimated growth rate from the literature fell between the expert-elicited estimates for an average and a good year.

For most parameters, there was great variation among expert estimation, as illustrated in Figs. 3 and 4, which also led to the difference among aggregation methods.

Based on our analysis, the mean estimated growth rate (λ_s) ranged

$$\begin{bmatrix}
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & \frac{[(1-nest)*ClutchSize\ *S_E*R*S_A]}{2} & \frac{[(1-nest)*ClutchSize\ *S_E*R*S_A]}{2} \\
S_H & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & S_{J1} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & S_{J2} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & S_{J3} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & S_{J3} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & S_{J3} & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & S_{J6} & 0 & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & S_{J6} & 0 & 0 & 0 & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & S_{J6} & 0 & 0 & 0 & 0 & 0 \\
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0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & S_{J6} & 0 & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & S_{J6} & 0 & 0 \\
0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & 0 & S_A & S_A
\end{bmatrix}$$

Fig. 2. Example matrix model assuming age of first reproduction is 14 years. This model takes into account juvenile survival categories. Symbols are defined in Table 2.

Table 3
Population growth rate estimates based on average values.

	Literature Values	Expert Values – Average Year	Expert Values – Good Year	Expert Values – Bad Year
One Juvenile Class	$\lambda = 0.951$	$\lambda = 0.912$	$\lambda = 0.967$	$\lambda = 0.750$
Multiple Juvenile Classes	–	$\lambda = 0.910$	$\lambda = 0.970$	$\lambda = 0.751$

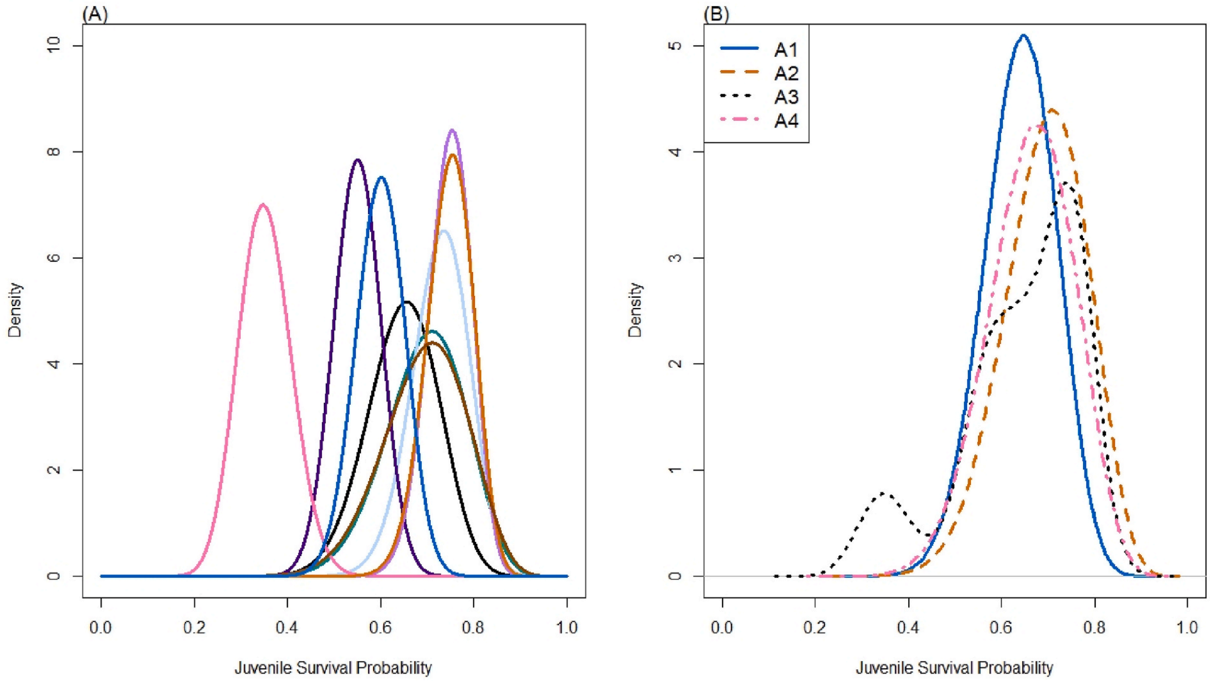

Fig. 3. Beta distributions fitted to the elicited quantiles obtained from nine experts (A; colored lines) and for the three aggregations methods (B; A1, A2,A3, and A4) for juvenile survival during "average" years.

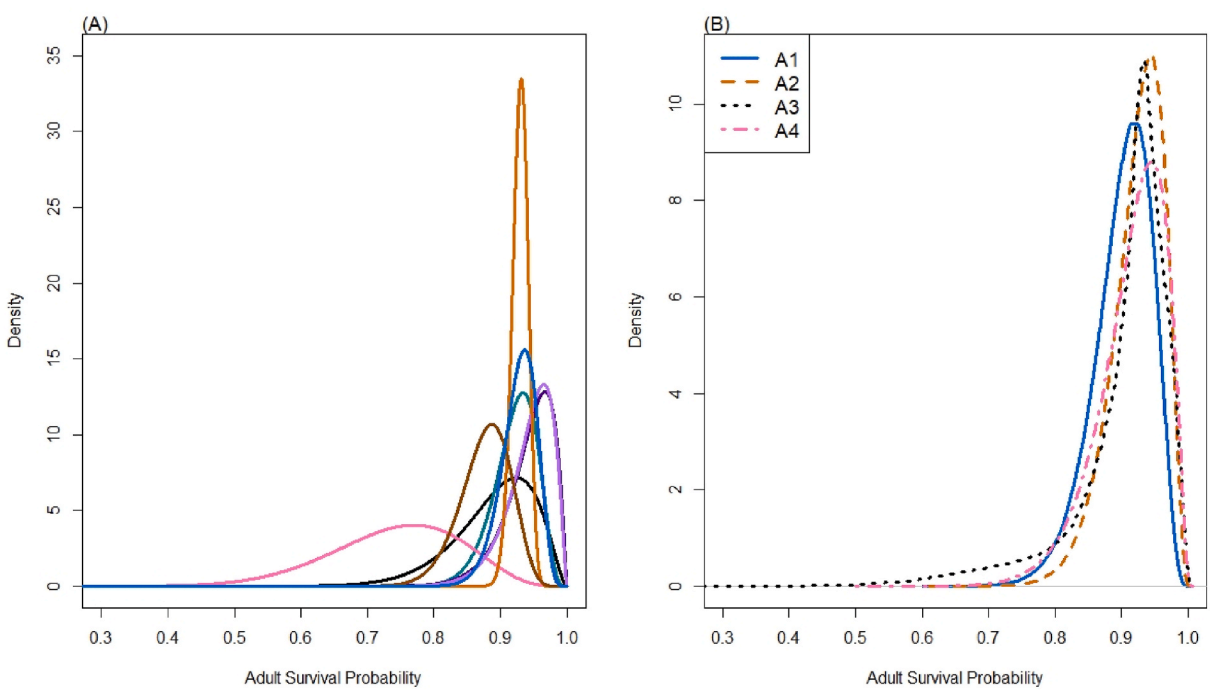

Fig. 4. Beta distributions fitted to the elicited quantiles obtained from nine experts (A; colored lines) and for the three aggregations methods (B; A1, A2,A3, and A4) for adult survival during "average" years.

from 0.78 to 0.798 for a bad year, from 0.907 to 0.922 for an average year, and from 0.963 to 0.976 in a good year (Table 4). The estimate based on the literature values fell between an average and a good year at 0.952. The upper 95% confidence limit of these mean values exceeded 1.0 for each aggregation method and matrix formulation in a good year, as well as with the literature values, indicating the possibility of a growing population within the range of the confidence interval. However, all other scenarios indicated a declining population. In general, there was little difference in estimates between the different matrix formulations (i.e., fixed age of first reproduction at 14 years old vs. variable age or including a single juvenile survival class vs. breaking juvenile survival down into four classes based on age). However, there were differences in estimates between the four aggregation methods. When data were aggregated by the mean before fitting the distribution (*A1*), estimated growth rates were lower overall, but they also had less variation as shown by the smaller standard deviations or coefficients of

Table 4
Deterministic population growth rate estimates based on the 50,000 matrices with input parameters based on fitted distributions for good, average, and bad years.

			Good				Average				Bad			
			Mean λ	Median λ	SD λ	95% CI λ	Mean λ	Median λ	SD λ	95% CI λ	Mean λ	Median λ	SD λ	95% CI λ
Literature Values							0.952	0.957	0.036	(0.870, 1.010)				
Expert Values	A1 method	1 Juvenile Class Variable age	0.966	0.968	0.041	(0.879, 1.042)	0.907	0.912	0.042	(0.811, 0.972)	0.748	0.751	0.054	(0.636, 0.847)
		4 Juvenile Classes Variable age	0.965	0.969	0.031	(0.896, 1.016)	0.907	0.912	0.041	(0.815, 0.971)	0.749	0.751	0.053	(0.640, 0.847)
		4 Juvenile Classes Fixed age at 14	0.964	0.968	0.031	(0.894, 1.015)	0.907	0.912	0.041	(0.815, 0.972)	0.749	0.751	0.054	(0.639, 0.847)
	A2 method	1 Juvenile Class Variable age	0.982	0.983	0.037	(0.903, 1.054)	0.932	0.937	0.038	(0.844, 0.989)	0.798	0.801	0.049	(0.694, 0.884)
		4 Juvenile Classes Variable age	0.983	0.986	0.028	(0.919, 1.028)	0.929	0.934	0.037	(0.842, 0.984)	0.798	0.801	0.048	(0.696, 0.884)
		4 Juvenile Classes Fixed age at 14	0.982	0.986	0.028	(0.917, 1.026)	0.929	0.934	0.037	(0.842, 0.984)	0.798	0.801	0.049	(0.696, 0.884)
	A3 method	1 Juvenile Class Variable age	0.976	1.002	0.080	(0.754, 1.071)	0.909	0.931	0.077	(0.670, 0.988)	0.753	0.799	0.141	(0.459, 0.921)
		4 Juvenile Classes Variable age	0.970	0.992	0.069	(0.771, 1.043)	0.911	0.928	0.063	(0.725, 0.987)	0.756	0.800	0.134	(0.497, 0.920)
		4 Juvenile Classes Fixed age at 14	0.969	0.992	0.071	(0.762, 1.040)	0.911	0.928	0.065	(0.719, 0.988)	0.755	0.800	0.136	(0.490, 0.921)
	A4 method	1 Juvenile Class Variable age	0.974	0.993	0.073	(0.790, 1.083)	0.922	0.930	0.048	(0.807, 0.990)	0.792	0.799	0.077	(0.624, 0.921)
		4 Juvenile Classes Variable age	0.965	0.986	0.062	(0.805, 1.040)	0.920	0.928	0.047	(0.808, 0.987)	0.792	0.799	0.076	(0.626, 0.921)
		4 Juvenile Classes Fixed age at 14	0.963	0.986	0.065	(0.795, 1.038)	0.920	0.928	0.048	(0.808, 0.988)	0.792	0.799	0.077	(0.625, 0.921)

variation (CV). However, when data were instead aggregated by the median (*A2*), estimated growth rates tended to be greater and less variable. The other two aggregation methods when all expert values were used, estimated growth rates fell between methods *A1* and *A2*, but with greater uncertainty (i.e., greater CV). When all expert values were used but a second distribution was fit to the quantiles of the first distribution for each parameter (*A4*), estimated growth rates were higher than when only a single distribution was fit to all of the expert values (*A3*).

Stochastic population growth rates were also estimated using the expert-elicited values with the four aggregation methods (Table 5). In this situation, age of first reproduction was fixed at 14 years of age, the average age of first reproduction. In all situations estimated stochastic growth rates indicated a declining population. Estimates were highest for the *A3* method, followed by the *A2* method, *A4* method, and then the *A1* method. When juvenile classes were split into four age classes instead of one, estimates of stochastic growth rate were higher, but still below one.

Lastly, we used a sensitivity analysis to understand which parameters had the largest effect on the estimates of population growth rate (Fig. 5). Using the average value for each parameter, we allowed one parameter to vary at a time and examined the effect on the estimated population growth rate. Adult survival had the largest effect, with the population growth rate varying from 0 to 1 depending on the value of adult survival. Juvenile survival and hatchling survival had smaller effects, with population growth rate only varying from 0.90 to 1.02 as juvenile survival varied from 0 to 1 and from 0.91 to 0.945 as hatchling survival varied from 0 to 1. For the hatchling survival scenario, we also fixed the nest survival to 1 as this would simulate a situation where management actions were implemented to ensure the survival of nests and hatchling turtles. However, even if nest survival is 100% and hatchling survival is 100% the estimated population growth rate will still not reach a stable or increasing population. If juvenile survival reaches 100% the population growth rate slightly passes 1 indicating a slightly growing population, but if adult survival reaches 100%, the population only reaches

Table 5
Stochastic population growth rates.

Aggregation Method	# Of Juvenile Classes	Mean λ	Median λ	SD λ	95% CI λ
A1	1 Juvenile Class	0.857	0.858	0.028	(0.795, 0.907)
A1	4 Juvenile Classes	0.861	0.861	0.026	(0.803, 0.910)
A2	1 Juvenile Class	0.889	0.890	0.024	(0.839, 0.932)
A2	4 Juvenile Classes	0.892	0.893	0.023	(0.845, 0.934)
A3	1 Juvenile Class	0.900	0.902	0.024	(0.846, 0.939)
A3	4 Juvenile Classes	0.917	0.919	0.020	(0.873, 0.951)
A4	1 Juvenile Class	0.874	0.881	0.047	(0.766, 0.947)
A4	4 Juvenile Classes	0.876	0.881	0.043	(0.779, 0.947)

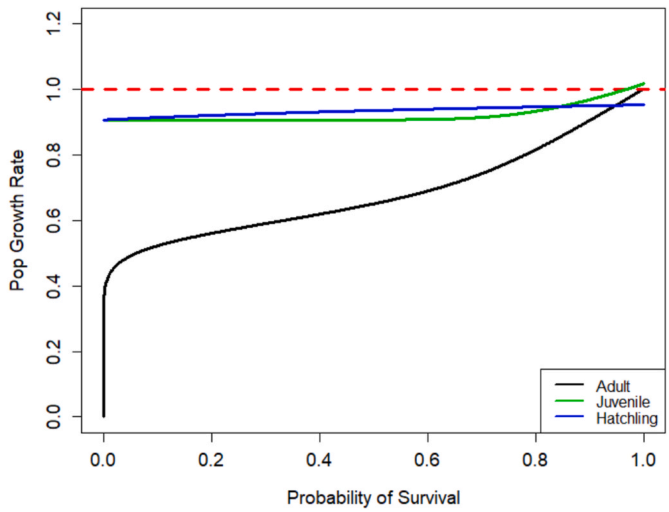

Fig. 5. Sensitivity plots showing the effect of varying adult survival, juvenile survival, or hatchling survival on estimated population growth rate. Dotted red lines mark population growth rate of 1.0 (i.e., a stable population). (For interpretation of the references to color in this figure legend, the reader is referred to the Web version of this article.)

stability.

4. Discussion

Conservation decisions such as those under the U.S. Endangered Species Act for candidate assessment, listing, consultations, and recovery of species can have important implications; yet often these decisions must be made “solely on the basis of the best scientific and commercial data available” despite major uncertainties (U.S. Fish and Wildlife Service, 2016). For instance, some of these species are elusive and poorly studied (particularly the ones that are rapidly declining but have not been federally listed; Lindenmayer et al., 2013), and it is often difficult to assess how these species will respond to environmental changes and future threats. Expert elicitation can be a useful tool to help with the population assessment as part of the ESA listing and recovery process.

The expert elicitation process used for wood turtles provided an alternative to relying solely on estimates from the literature. There are numerous limitations to the information from the literature to estimate the population growth rate: (1) the vital rates were obtained from study sites that may not have been representative of the population of interest (for example the best studied populations may exist in areas that benefit from better environmental protections); (2) historic estimates are not necessarily a good reflection of the future, if the goal is forecasting; or (3) several of the vital rates from the literature did not use rigorous estimators that properly address important sources of error such as imperfect detection. Thus, using expert elicitation while considering uncertainty, provides useful complementary insights about the future of the study population. While some parameter estimates were comparable with what was found in the literature, other parameters were not. For example, juvenile survival estimates from the experts for good, average, and bad years were all lower than the values found in the literature. Similarly, the estimate of the age of first reproduction was also higher in the literature. Conversely, estimates from the experts for survival of hatchlings were higher than the one value found in the literature. The lower estimates may have reflected that the experts believed the populations reported in the literature are not representative of the population of interest (i.e., experts were asked to provide estimates based on the representative area in the center of the range (Fig. 1)), but may also represent a belief that current threats (e.g., habitat loss, poaching, changes associated with climate) may depress these vital rates and were not considered in existing publications.

Our estimate of population growth rate based on parameter values from the literature (λ_{mean} = 0.952, 95% CI: 0.87–1.01) does not conclusively reject the hypothesis of a rapidly declining population or a stable or even very slowly growing population (i.e., by 1% based on the upper 95% CI). In contrast, our results from the expert-elicited estimates suggest wood turtle population decline regardless of aggregation method or matrix model formulation. In fact, even the upper 95% CI of the stochastic population growth rate did not include a lambda of 1.0 (Table 5). A few possible explanations include: (1) several of the survival rates from the literature did not account for imperfect detection, and the experts may have anchored on these (biased) values (we note that we had several discussions about this issue, but some anchoring effect may have remained); (2) the experts may have been overly pessimistic about the future; or (3) the experts are correct, and the future is very bleak for this population (for example under *A4* [4 Juvenile classes] in Table 5, λ_{mean} = 0.88, 95% CI: 0.78–0.95; which would indicate a 5% annual decline even under the 97.5 percentile value of λ). Interestingly, there are differences in the temporal scope for inference between the literature-based estimates that may in fact provide insights about historical changes (e.g., historical decline), whereas the expert-based estimates were forward looking and therefore informed us about future potential declines given current demographic rates. In any case, we stress the importance of considering the uncertainty estimates as opposed to focusing on measure of central tendencies, particularly given the high level of uncertainty for our study.

Although the population growth rate estimates from the four aggregation methods resulted in an estimated decline, there were notable differences among these methods. The variation in the results points to the importance of careful consideration about the aggregation techniques used. Method *A1* led to the lowest deterministic and stochastic population growth rate estimates, while *A2* led to the highest deterministic estimates, and *A3* led to the highest stochastic estimates. One benefit of method *A2* (median-based approach) over method *A1* (mean-based approach) is that *A2* may prevent the undue influence of outliers. When estimating the deterministic growth rate, Methods *A1* and *A2*, where values were aggregated before fitting the distribution, led to less uncertainty (lower SD and CV), than for Methods *A3* and *A4*. This is not surprising as of the four methods considered, *A3* and *A4* are the most explicit about considering uncertainty within and among experts. Method *A3* can be helpful to identify disagreement among groups of experts (e.g., due to competing hypotheses) which could be reflected by multimodal distributions (Morgan, 2014). Method *A4* is appealing in the sense that it may more explicitly account for variation among the experts (than Methods *A1* and *A2*) and yet avoids the potential downsides of multimodal distributions (Method *A3*), which may not be a good approximation of vital rates. Multimodal distributions may also lead to patterns that are counterintuitive. It is worth pointing out that there is a tradeoff between methods that leads to distribution that are either too precise or too imprecise. Indeed, given that we set the confidence levels for the three-point expert elicitation process at 95%, we would theoretically expect that the true value should be outside of the 95% interval 5% of the time. Methods A3 and A4 may be at a greater risk of leading to estimates that are too imprecise. Conversely, aggregation methods such as A1 and A2 may be at a great risk of returning estimates that are too precise. Additionally we note that this pattern in variation among the four methods may not be consistent for other case studies; therefore it may be useful to assess the sensitivity of the population growth rate to these alternative methods. Managers can then consider this source of uncertainty when assessing the population status. In addition to the four methods presented in this paper, there are alternative aggregation method used in ecology. These include weighted aggregation methods, where estimates from different expert are given weight based on criteria such as experience level, or behavioral aggregation methods, where experts work together to reach a consensus on each parameter estimate (Hemming et al., 2020). One way to evaluate the performance of alternative aggregation approaches is to use seed questions (also known as calibration questions, which are quantities known to the elicitation coach but unknown to the experts) during training exercises, and compare the results from the aggregation methods with the known values (Colson and Cooke, 2018).

Conducting a sensitivity or elasticity analyses can be helpful for determining management actions that could have the largest effect on population growth rate. Our sensitivity and elasticity analyses supported the notion that population growth rate of wood turtles is most sensitive to changes in adult survival, which is a typical observation for long living species (Caswell, 2006; Folt et al., 2016; Rachmansah et al., 2020; Runge et al., 2007, 2017). An implication of these results is that interventions to increase adult turtle survival by reducing road mortality, preventing mortality from agricultural activities, or curbing removal of individuals by addressing illicit trade could have large effects on increasing population growth rate. Increasing juvenile survival rates and hatchling survival rates only had minimal effects on the turtle population (though it is worth noting that an increasing population may only be reached if juvenile survival is also increased).

Although our analyses accounted for important sources of uncertainty (such as environmental stochasticity and parametric uncertainty) and provided us with some useful insights, it is worth considering some of the limitations. Firstly, our predictive abilities would improve as more rigorous empirical estimates of vital rates become available. Secondly, we did not account for potential covariances among the experts (Johnson et al., 2017) which could affect the precision of our estimates; positive correlation would tend to lead to more precise estimates, therefore ignoring this effect as we did would lead to wider uncertainty bounds. Thirdly, given the large number of parameters included in each model (e.g., 36 parameters [for the model with four juvenile stages]), for each of the nine experts, and for four methodologies) we automated the fitting of distributions to the available data. This automated process can be an additional source of error, and it is therefore helpful to validate parameters, particularly for the vital rates that contribute the most to population growth rate. For example, the weight assigned to each quantile, can have a strong influence on the fitted distribution. Finally, we did not account for demographic stochasticity, temporal autocorrelation, and covariance among vital rates which if accounted for would be expected to lead to lower estimates of population growth. We found our estimates of central tendencies to be already low. Indeed a 15% rate of annual decline would be extremely rapid, but as noted earlier we encourage readers to focus on the uncertainty bounds instead of the means or medians. For instance, the upper 95% CI of some of the methods used suggest a 5% rate of decline. We also note that as is the case with most estimates of population growth rates based on matrix population models, ignoring the immigration process (as we did) into the population can lead to growth rates that are negatively biased.

Nevertheless, we use expert elicitation as a useful tool to help managers assess the population status of wood turtle populations when data are lacking, and demonstrate how this approach is particularly useful when accounting for important sources of uncertainty. As mentioned by other authors (Colson and Cooke, 2018), the rigor of the protocol used for the elicitation can influence the results. Accordingly, here we have also quantified the variation among aggregation methods and pointed out considerations about the automated process for curve fitting to the elicited quantiles. We recognize there are other potentially important sources of uncertainty (e.g., model uncertainty [such as different stage structures], demographic stochasticity) that may be worth considering when conducting future population status assessment. The technique used to aggregate data emerged as one of these important sources of uncertainty. These findings are applicable for other population models used for conservation and management, such as various forms of population viability analyses (Beissinger and McCullough, 2002; Caswell, 2006; Martin et al., 2017; Morris and Doak, 2002; Runge et al., 2017) or for identifying optimal decisions based on the best scientific information available (Fackler et al., 2014; Johnson et al., 2017; O'Donnell et al., 2020).

Credit author statement

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Data availability

Data is available through the Science Base digital repository (Moore et al., 2021).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jenvman.2022.114453.

References

Adkins Giese, C.L., Greenwald, D.N., Curry, T., 2012. Before the Secretary of the Interior: Petition to List 53 Amphibians and Reptiles in the United States as Threatened or Endangered Species under the Endangered Species Act. Center for Biological Diversity Report.

Beissinger, S.R., McCullough, D.R., 2002. Population Viability Analysis. University of Chicago Press.

Belgorodski, N., Greiner, M., Tolksdorf, K., Schueller, K., Flor, M., Gohring, L., Greiner, M.M., 2017. rriskDistributions: Fitting Distributions to Given Data or Known Quantiles.

Bodie, J.R., Semlitsch, R.D., 2000. Size-specific mortality and natural selection in freshwater turtles. Copeia 2000 (3), 732–739.

Canessa, S., Converse, S.J., West, M., Clemann, N., Gillespie, G., McFadden, M., Silla, A. J., Parris, K.M., McCarthy, M.A., 2016. Planning for ex situ conservation in the face of uncertainty. Conserv. Biol. 30 (3), 599–609. https://doi.org/10.1111/cobi.12613.

Caswell, H., 2006. Matrix Population Models. Sinauer.

Colson, A.R., Cooke, R., 2018. Expert elicitation: using the classical model to validate experts' judgments. Rev. Environ. Econ. Pol. https://doi.org/10.1093/reep/rex022.

Converse, S.J., Moore, C.T., Folk, M.J., Runge, M.C., 2013. A matter of tradeoffs: reintroduction as a multiple objective decision. J. Wildl. Manag. 77 (6), 1145–1156. https://doi.org/10.1002/jwmg.472.

Cummings, J.W., Parkin, M., Zelenak, J., Bell, H., Broderdorp, K., Holt, B., McCollough, M., Smith, T., 2020. Applying expert elicitation of viability and persistence to a lynx species status assessment. Conservation Science and Practice 2 (11), e2284. https://doi.org/10.1111/csp2.284.

Drechsler, M., Eppink, F.V., Wätzold, F., 2011. Does proactive biodiversity conservation save costs? Biodivers. Conserv. 20 (5), 1045–1055.

Ernst, C.H., Lovich, J.E., 2009. Turtles of the United States and Canada. JHU Press.

Fackler, P.L., Pacifici, K., Martin, J., McIntyre, C., 2014. Efficient use of information in adaptive management with an application to managing recreation near golden eagle nesting sites. PLoS One 9 (8), e102434. https://doi.org/10.1371/journal.pone.0102434.

U.S. Fish and Wildlife Service, 2016. USFWS Species Status Assessment Framework: an Integrated Analytical Framework for Conservation. Version 3.4.

Folt, B., Jensen, J.B., Teare, A., Rostal, D., 2016. Establishing reference demography for conservation: a case study of Macrochelys temminckii in Spring Creek, Georgia. Herpetol. Monogr. 30 (1), 21–33.

Grant, E.H.C., Zipkin, E.F., Nichols, J.D., Campbell, J.P., 2013. A strategy for monitoring and managing declines in an amphibian community. Conserv. Biol. 27 (6), 1245–1253.

Hanea, A.M., McBride, M.F., Burgman, M.A., Wintle, B.C., Fidler, F., Flander, L., Twardy, C.R., Manning, B., Mascaro, S., 2017. I nvestigate D iscuss E stimate A ggregate for structured expert judgement. Int. J. Forecast. 33 (1), 267–279. https://doi.org/10.1016/j.ijforecast.2016.02.008.

Harding, J.H., Bloomer, T.J., 1979. The wood turtle, Clemmys insculpta... A natural history. Bulletin of the New York Herpetological Society 15 (1), 9–26.

Haskell, A., Graham, T.E., Griffin, C.R., Hestbeck, J.B., 1996. Size related survival of headstarted redbelly turtles (Pseudemys rubriventris) in Massachusetts. J. Herpetol. 30 (4), 524–527.

Hemming, V., Hanea, A.M., Walshe, T., Burgman, M.A., 2020. Weighting and aggregating expert ecological judgments. Ecol. Appl. 30 (4), e02075 https://doi.org/10.1002/eap.2075.

Hora, S.C., Fransen, B.R., Hawkins, N., Susel, I., 2013. Median aggregation of distribution functions. Decis. Anal. 10 (4), 279–291. https://doi.org/10.1287/deca.2013.0282.

Hostetler, J.A., Martin, J., Kosempa, M., Edwards, H.H., Rood, K.A., Barton, S.L., Runge, M.C., 2021. Reconstructing population dynamics of a threatened marine mammal using multiple data sets. Sci. Rep. 11 (1), 2702. https://doi.org/10.1038/s41598-021-81478-z.

Johnson, F.A., Smith, B.J., Bonneau, M., Martin, J., Romagosa, C., Mazzotti, F., Waddle, H., Reed, R.N., Eckles, J.K., Vitt, L.J., 2017. Expert elicitation, uncertainty, and the value of information in controlling invasive species. Ecol. Econ. 137, 83–90. https://doi.org/10.1016/j.ecolecon.2017.03.004.

Jones, M.T., 2009. Spatial Ecology, Population Structure, and Conservation of the Wood Turtle. Glyptemys insculpta, New England in central.

Jones, M.T., Willey, L.L. (Eds.), 2021. *Biology And Conservation Of the Wood Turtle.* Northeast Association of Fish and Wildlife Agencies.

Lindenmayer, D.B., Piggott, M.P., Wintle, B.A., 2013. Counting the books while the library burns: why conservation monitoring programs need a plan for action. Front. Ecol. Environ. 11 (10), 549–555. https://doi.org/10.1890/120220.

Lyon, A., Wintle, B.C., Burgman, M., 2015. Collective wisdom: methods of confidence interval aggregation. J. Bus. Res. 68 (8), 1759–1767. https://doi.org/10.1016/j.jbusres.2014.08.012.

Martin, J., Kitchens, W.M., Cattau, C.E., Oli, M.K., 2008. Relative importance of natural disturbances and habitat degradation on snail kite population dynamics. Endanger. Species Res. 6 (1), 25–39. https://doi.org/10.3354/esr00119.

Martin, J., Runge, M.C., Flewelling, L.J., Deutsch, C.J., Landsberg, J.H., 2017. An expert elicitation process to project the frequency and magnitude of Florida manatee mortality events caused by red tide (Karenia brevis). In: An Expert Elicitation Process to Project the Frequency and Magnitude of Florida Manatee Mortality Events Caused by Red Tide (Karenia Brevis) (USGS Numbered Series No. 2017–1132; Open-File Report, vols. 2017–1132. U.S. Geological Survey, p. 28. https://doi.org/10.3133/ofr20171132.

McBride, M.F., Garnett, S.T., Szabo, J.K., Burbidge, A.H., Butchart, S.H.M., Christidis, L., Dutson, G., Ford, H.A., Loyn, R.H., Watson, D.M., Burgman, M.A., 2012. Structured elicitation of expert judgments for threatened species assessment: a case study on a continental scale using email. Methods in Ecology and Evolution 3 (5), 906–920. https://doi.org/10.1111/j.2041-210X.2012.00221.x.

McGowan, C.P., Runge, M.C., Larson, M.A., 2011. Incorporating parametric uncertainty into population viability analysis models. Biol. Conserv. 144 (5), 1400–1408. https://doi.org/10.1016/j.biocon.2011.01.005.

Moore, J.F., Martin, J., Waddle, J.H., Grant, E.H.C., Fleming, J., Bohnett, E., Akre, T.S.B., Brown, D.J., Jones, M.T., Oxenrider, K., Tur, A., Willey, L.L., Johnson, F.A., 2021. Data from: "Evaluating the Effect of Expert Elicitation Techniques on Population Status Assessment in the Face of Large Uncertainty. *U.S. Geological Survey Data Release*. https://doi.org/10.5066/P99F5J2B.

Morgan, M.G., 2014. Use (and abuse) of expert elicitation in support of decision making for public policy. Proc. Natl. Acad. Sci. Unit. States Am. 111 (20), 7176–7184. https://doi.org/10.1073/pnas.1319946111.

Morris, W.F., Doak, D.F., 2002. Quantitative Conservation Biology: Theory and Practice of Population Viability Analysis. Sinauer.

Mothes, C.C., Howell, H.J., Searcy, C.A., 2020. Habitat suitability models for the imperiled wood turtle (Glyptemys insculpta) raise concerns for the species' persistence under future climate change. Global Ecology and Conservation 24, e01247.

Nichols, J.D., 2019. Confronting uncertainty: contributions of the wildlife profession to the broader scientific community. J. Wildl. Manag. 83 (3), 519–533. https://doi.org/10.1002/jwmg.21630.

O'Donnell, K.M., Fackler, P.L., Johnson, F.A., Bonneau, M.N., Martin, J., Walls, S.C., 2020. Category count models for adaptive management of metapopulations: case study of an imperiled salamander. Conservation Science and Practice 2 (4), e180. https://doi.org/10.1111/csp2.180.

Powell, R., Conant, R., Collins, J.T., 2016. Peterson Field Guide to Reptiles and Amphibians of Eastern and Central North America. Houghton Mifflin Harcourt.

R Development Core Team, 2019. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing. http://www.R-project.org.

Rachmansah, A., Norris, D., Gibbs, J.P., 2020. Population dynamics and biological feasibility of sustainable harvesting as a conservation strategy for tropical and temperate freshwater turtles. PLoS One 15 (2), e0229689.

Regan, H.M., Ben-Haim, Y., Langford, B., Wilson, W.G., Lundberg, P., Andelman, S.J., Burgman, M.A., 2005. Robust decision-making under severe uncertainty for conservation management. Ecol. Appl. 15 (4), 1471–1477. https://doi.org/10.1890/03-5419.

Rigby, R.A., Stasinopoulos, D.M., 2005. Generalized additive models for location, scale and shape (with discussion). Applied Statistics 54 (3), 507–554.

Robinson, K.F., Fuller, A.K., Hurst, J.E., Swift, B.L., Kirsch, A., Farquhar, J., Decker, D.J., Siemer, W.F., 2016. Structured decision making as a framework for large-scale wildlife harvest management decisions. Ecosphere 7 (12), e01613. https://doi.org/10.1002/ecs2.1613.

Runge, M.C., Sanders-Reed, C.A., Fonnesbeck, C.J., 2007. *A Core Stochastic Population Projection Model for Florida Manatees (*Trichechus manatus Latirostris*)*. US Geological Survey. https://pubs.er.usgs.gov/publication/ofr20071082.

Runge, M.C., Converse, S.J., Lyons, J.E., 2011. Which uncertainty? Using expert elicitation and expected value of information to design an adaptive program. Biol. Conserv. 144 (4), 1214–1223.

Runge, M.C., Sanders-Reed, C.A., Langtimm, C.A., Hostetler, J.A., Martin, J., Deutsch, C. J., Ward-Geiger, L.I., Mahon, G.L., 2017. Status and threats analysis for the Florida manatee (Trichechus manatus latirostris). U.S. Geological Survey.

Stasinopoulos, M., Rigby, R., 2020. Gamlss.dist: Distributions for Genearlized Additive Models for Location Scale and Shape. R Package Version 5.1-6. http://CRAN.R-project.org/package=gamlss.dist.

Stubben, C.J., Milligan, B.G., 2007. Estimating and analyzing demographic models using the popbio package in R. J. Stat. Software 22 (11).

Sutherland, W.J., Burgman, M., 2015. Policy advice: use experts wisely. Nature News 526 (7573), 317. https://doi.org/10.1038/526317a.

Tuljapurkar, S.D., Orzack, S.H., 1980. Population dynamics in variable environments I. Long-run growth rates and extinction. Theor. Popul. Biol. 18 (3), 314–342. https://doi.org/10.1016/0040-5809(80)90057-X.

van Dijk, P.P., Harding, J., 2011. Glyptemys Insculpta. *IUCN Red List Of Threatened Species*. Version 2011.2. http://www.iucnredlist.org.

Williams, B.K., 1997. Approaches to the management of waterfowl under uncertainty. Wildl. Soc. Bull. 25 (3), 714–720, 1973-2006.

Williams, B.K., 2001. Uncertainty, learning, and the optimal management of wildlife. Environ. Ecol. Stat. 8 (3), 269–288. https://doi.org/10.1023/A:1011395725123.

Williams, B.K., Nichols, J.D., Conroy, M.J., 2002. Analysis and Management of Animal Populations. Academic Press.