Journal of Choice Modelling 47 (2023) 100414

Contents lists available at ScienceDirect

Journal of Choice Modelling

journal homepage: www.elsevier.com/locate/jocm

Estimating a model of forward-looking behavior with discrete choice experiments: The case of lifetime hunting license demand

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ARTICLE INFO

Keywords:
Discrete choice experiment
Dynamic discrete choice
Recreation demand
Stated preference
Wildlife

ABSTRACT

Sales of deer licenses, one of the most important revenue sources for wildlife management at the Indiana Department of Natural Resources (IDNR), have been declining for a decade. To increase its revenue, the IDNR is considering introducing a new lifetime deer license for sale. This license would allow hunters to harvest deer (and possibly other species) each year for the rest of their lives in exchange for a relatively large up-front fee. The forward-looking nature of the decision to buy a lifetime license means hunters' choice behavior is necessarily dynamic. Prior work estimates preferences for long-lived, durable goods using standard discrete choice experiments underpinned by static models. We derive a dynamic discrete choice model of lifetime license purchases. Our model informs the design of a novel, dynamic discrete choice experiment, generating data that allows us to consistently estimate individuals' forward-looking preferences for lifetime hunting licenses. We use our model to estimate the price of lifetime licenses that maximizes IDNR revenues.

1. Introduction

Discrete choice experiments (DCEs) are widely used to estimate consumer demand for hypothetical goods and their attributes. This approach works by simulating a hypothetical market in which consumers are asked to choose one of several mutually-exclusive alternatives based on their preferences (Holmes et al., 2017). Defining alternatives as a set of attributes with one or more levels, researchers can infer individuals' preferences by analyzing how they trade off different levels of each attribute when making choices about which goods they would hypothetically buy.

We design a novel DCE that accounts for forward-looking behavior to estimate a choice model for hypothetical lifetime deer hunting licenses among hunters in the U.S. state of Indiana. As the name implies, this license would give hunters the right to harvest a fixed number of deer per season for the rest of their lives in exchange for paying an up-front fee equal to many times the price of existing annual licenses.

The fact that (i) the present value of utility hunters of different ages will receive from a lifetime license depends on their ages—and, hence, the number of remaining years they expect to hunt—and (ii) the decision to purchase a lifetime license obviates the need to purchase future licenses makes this a simple form of optimal stopping problem akin to Rust (1987). Put differently, the choice problem we simulate with our DCE is necessarily dynamic. Prior work commonly uses DCEs to estimate individuals' preferences for other types of long-lived, durable goods like personal vehicles (Costa et al., 2019; Byun et al., 2018; de Jong et al., 2009), home appliances (Lang

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https://doi.org/10.1016/j.jocm.2023.100414
Received 12 October 2022; Received in revised form 11 March 2023; Accepted 25 April 2023
Available online 3 May 2023

et al., 2021; Zha et al., 2020) and capital-intensive farm production systems (Howard et al., 2023; Gramig and Widmar 2018; Olynk et al., 2012). However, none of this work explicitly models forward-looking behavior on the part of DCE subjects. The analytical model underpinning this prior work is McFadden's (1974) random utility maximization model which, in its standard form, assumes decisionmakers are myopic—or, at the very least, is not explicitly dynamic.

Ignoring forward-looking behavior in designing a DCE is of no consequence if the values of relevant state variables underlying the simulated decision problem are independent of subjects' current choices (in which case the decision problem is not dynamic in any meaningful sense). Less trivially, if the DCE is designed in such a way that any possible decision leads to one or more absorbing states then, conditional on their contemporaneous choice, the subject's entire future becomes known up to an expectation of the state variables. If neither of these conditions hold—and it is not evident that they do in prior work—then we may expect biased estimates of subjects' preference parameters, which will also impact the levels of any quantities estimated from them (e.g., willingness to pay or market shares).

We design our DCE in accordance with an analytical model that explicitly considers subjects' forward-looking behavior when evaluating lifetime license purchases. Our design is inspired by the one-step-ahead conditional choice probability approach of Hotz and Miller (1993). Specifically, we show hunters a take-it-or-leave-it lifetime license offer. If the hunter chooses to purchase a lifetime license, he or she receives the same utility from that lifetime license each year for the rest of his or her life. If the hunter does not buy a lifetime license, he or she gets the level of utility that corresponds to the *status quo* combination of licenses he or she buys every year. Our approach effectively turns a dynamic problem into a static one by eliminating subjects' need to consider choices beyond the present period. It also allows us to derive the present value of future utility a hunter receives from either of the choices—and hence hunters' choice probabilities—in closed form, which is convenient for estimation.

Our empirical approach is informed by the extensive literature on dynamic discrete choice models (see Aguirregabiria and Mira (2010) and Eckstein and Wolpin (1989) for reviews). This prior work primarily relies on observational data; to our knowledge, we are the first to apply these insights in the context of a DCE. This study also makes an empirical contribution by being the first to use DCEs to value lifetime hunting license attributes. DCEs are commonly used to value attributes of big game hunting, including game animal density (Boxall and Macnab 2011; Boxall et al., 1996; Haener et al., 2001; Horne and Petäjistö 2003; Hunt et al., 2005; Kerr and Abell, 2016), the probability of successful harvest (Hussain et al., 2003; Mackenzie 1990), and policy choices like bag limits and season length (Serenari et al., 2019).

In what follows, we first provide background on deer hunting in Indiana to give context to our choice model, which we develop in Section 3. We then describe our DCE and data. Section 4 describes our estimation approach. Section 5 presents parameter estimates from our dynamic model. We compare these to estimates from a myopic model and explain why they generally differ. Section 6 provides an overview and conclusion.

2. Deer hunting in Indiana

The Indiana Department of Natural Resources' (IDNR's) Division of Fish & Wildlife has been charged with conservation of land and wildlife populations since 1965. The deer hunting season is composed primarily of three seasons: archery (early October to early January), firearm (mid-to late November), and muzzleloader (early to mid-December).[1] IDNR currently offers two types of licenses: a single-season license and a deer license bundle. Single-season licenses allow hunters to harvest a given number of deer—or a "bag limit"—in only one season. Bag limits vary by season but all permit harvest of at most one antlered deer.[2] Single-season deer licenses cost $24 for residents. The deer license bundle allows hunters to harvest up to three deer (only one of which can be antlered) across any season. This bundle license was first offered in 2012 and costs $65 for residents. Additionally, hunters can purchase bonus antlerless deer licenses which allow harvest of antlerless deer in excess of license-specific bag limits, subject to county-level harvest quotas. The first bonus antlerless license costs $24. Subsequent licenses are sold at a discount. All license fees have remained the same since 2002 when IDNR increased the single-season deer license from $13.75 to $24.

Funding for the Division of Fish & Wildlife is collected from two major sources: state funding and federal funding. State funding comes primarily from sales of hunting, fishing, and trapping licenses and is spent to manage species for fishing and hunting. The amount of state funding was $9.3 million in 2020 (IDNR 2022). However, sales of all hunting, fishing, and trapping licenses have declined 11 percent from 2011 to 2017, and deer license sales have declined 44 percent over the same period (IDNR 2017).

This decline in license sales threatens the stability of state conservation funding, which in turn threatens deer management—which depends financially and ecologically on recreational harvests (Brown et al., 2000; Peterson 2004; Schorr et al., 2014)—as well as wildlife research, habitat restoration, and maintenance of wildlife areas and public access sites. This is because the sale of deer licenses contributes significantly to DNR revenues. Indeed, the sale of hunting licenses accounts for 29 percent of IDNR funding, and deer licenses—which are relatively more expensive than other licenses—are the second-best-selling license type in Indiana (IDNR 2017; 2022).

To tackle this financial issue, IDNR announced hunting, fishing and trapping license fees for 2022–2023 would increase in December 2021.[3] Another solution IDNR is considering is to launch a new license: a lifetime deer license bundle. This license would

[1] There are other seasons such as reduction zone and youth deer seasons, the dates for which can vary from year to year. However, relatively few hunters hunt during these seasons.

[2] An antlered deer is a male deer with at least one antler that is at least three inches long. All other deer are considered "antlerless."

[3] The prices we use in our analysis are the previous license fees, which correspond to those that prevailed during the course of the study.

give hunters the right to harvest up to three deer (one antlered deer and two antlerless deer or three antlerless deer) per season in exchange for paying a large up-front fee, equal to many multiples of the price of an annual license. Lifetime licenses may also include licenses for harvesting various other species in addition to deer (e.g., fish or small game). These licenses may be attractive to customers who seek to avoid future deer hunting license price increases or who wish to give a lifetime license to a child or grandchild as a gift. Further, lifetime license revenues provide the IDNR with stable funding for wildlife management via federal tax programs which provide annual matching funds proportional to the number of licenses sold.

A lifetime deer license was previously offered for sale from 1981 to 2005. It took the form of a lifetime comprehensive hunting license, which covered all required hunting licenses and stamps—not just deer. In addition to a fishing or hunting license, a hunter with a lifetime comprehensive hunting license or lifetime comprehensive hunting and fishing license could harvest up to one antlered and one antlerless deer, depending on his or her equipment. Approximately 44,000 lifetime licenses were sold, about 59 percent of which were the lifetime comprehensive hunting license.

We cannot use data from previous lifetime license sales to estimate demand for the lifetime deer license bundles currently under consideration for two reasons. First, this license was different from the one IDNR is currently considering, as we describe later. Second, there is no meaningful variation in the license prices or other attributes (aside from option to add the lifetime fishing license). Every hunter, regardless of age or other characteristics, paid the same rate for each license, and this price was held constant over time. This implies that we cannot identify hunters' preference parameters over these attributes. We therefore use a DCE to estimate demand for lifetime deer bundles.

3. Methods

This section is divided into two parts. First, we derive a dynamic model of lifetime license choice. Second, we describe the design of the DCE that we use to elicit the data to estimate this model.

3.1. A model of lifetime license choice

A prospective hunter, indexed by i, who expects to hunt for T_i more years faces a choice of whether to (i) buy a lifetime deer hunting license j at time t or (ii) forego a lifetime license in exchange for their *status quo* choice (e.g., an annual deer hunting license). Without loss of generality, let the *status quo* alternative be $j = 0$. Let the set of lifetime licenses available to hunter i be $\mathscr{C}(\mathbf{H}_{it})$, where $\mathbf{H}_{it} = \{\mathbf{h}_{i0}, \mathbf{h}_{i1}, \ldots, \mathbf{h}_{it-1}\}$ is the hunter's choice history up to year t, $\mathbf{h}_{i\tau} = \{h_{ij\tau}\}_{\forall j \in \mathscr{C}(\mathbf{H}_{i\tau})}$ is a vector denoting the hunter's choice in period τ, and $h_{ij\tau} = 1$ if the hunter chooses license j in period τ and zero otherwise. The hunter's choice set depends on their choice history. If the hunter has never purchased a lifetime license at time t, then $h_{i0\tau} = 1$ and $h_{ij\tau} = 0\ \forall j \neq 0, \tau$ and their choice set is $\mathscr{C}(\mathbf{H}_{it}) = \{0, 1, \ldots, J\}$. If the hunter purchases lifetime license $j \neq 0$ in any year t, then their choice set effectively collapses to $\mathscr{C}(\mathbf{H}_{i\tau}) = \{j\} \forall \tau \geq t$ since they never need to buy another license.

Let the single-period flow utility from choice j be $V_{ijt} + \varepsilon_{ijt}$, which comprises a deterministic component, V_{ijt}, and a random, unobservable component, ε_{ijt}, assumed i.i.d. across individuals, license choices, and time periods. Hunters choose h_{ijt} each year to maximize the present value of their lifetime indirect utility, $\sum_{\tau=0}^{T_i} \sum_{j \in \mathscr{C}(\mathbf{H}_{it})} h_{ij\tau}[V_{ijt} + \varepsilon_{ij\tau}]\delta_i^{\tau}$, where δ_i is the discount factor. This is the hunter's dynamic decision problem. Let the present value of utility the hunter receives conditional on choice h_{ijt} be

$$V_{ijt} + \delta_i E\left(\sum_{\tau=1}^{T_i} \sum_{j' \in \mathscr{C}(\mathbf{H}_{i\tau})} h^*_{ij'\tau}\left[V_{ij'\tau} + \varepsilon_{ij'\tau}\right]\right) + \varepsilon_{ijt} = U_{ijt} + \varepsilon_{ijt}, \tag{1}$$

where $h^*_{ij't}$ is the hunter's optimal choice in year t and

$$U_{ijt} = V_{ijt} + \delta_i E\left(\sum_{\tau=1}^{T_i} \sum_{j' \in \mathscr{C}(\mathbf{H}_{i\tau})} h^*_{ij'\tau}\left[V_{ij'\tau} + \varepsilon_{ij'\tau}\right]\right) \tag{2}$$

is the conditional value function.

Given the random ε_{ijt} terms, the probability the hunter chooses alternative $j \in \mathscr{C}(\mathbf{H}_{it})$ in period t is

$$\pi_{ijt} = \Pr\left(U_{ijt} + \varepsilon_{ijt} \geq U_{ij't} + \varepsilon_{ij't} \forall j' \neq j\right). \tag{3}$$

We could derive this probability by solving a dynamic programming problem using backward recursion (Arcidiacono and Ellickson, 2011). Specifically, we could assume the shocks ε_{ijt} have a type-1 extreme value distribution such that we can write the expectation in (2) as

$$\ln\left(\sum_{j \in \mathscr{C}(\mathbf{H}_{it+1})} \exp\left(U_{ijt+1}\right)\right) + \gamma, \tag{4}$$

where γ is Euler's constant. We could then rewrite the conditional value function as.

$$U_{ijt} = V_{ijt} + \delta_i \left[\ln\left(\sum_{j' \in \mathscr{C}(\mathbf{H}_{it+1})} \exp\left(U_{ij't+1}\right) \right) + \gamma \right]. \tag{5}$$

Given the distributional assumption on ε_{ijt}, the resulting choice probability (3) is

$$\pi_{ijt} = \frac{e^{U_{ijt}}}{\sum_{j'} e^{U_{ij't}}}. \tag{6}$$

Solving (5) is computationally burdensome and is typically infeasible in a DCE setting as identification of the preference parameters in V_{ijt} usually requires observations of subjects' choices made over multiple periods and in multiple states of the world (i.e., given different choice histories; Reeling et al., 2020). This is not possible in our case given the one-shot nature of our DCE and that one's state depends on their purchase of a hypothetical good. Prior DCEs cited previously that are not explicitly based on a dynamic behavioral model effectively ignore the continuation value (i.e., the second term) in (2), specifying $U_{ijt} = V_{ijt}$. The consequence of doing this is to misattribute the continuation value from alternative j—which may reflect the utility from a completely different future choice j'—to the utility from j. As an extreme example, suppose hunter i's optimal decision path is to choose their *status quo* license in the current period and a lifetime license the following period, say, once an income constraint is relaxed. Estimates that perfectly rationalize this choice would make the value of V_{i0t} relatively large. This would make the *status quo* choice look relatively attractive even though, in reality, this estimate is simply capturing the continuation value from a different, future choice.

To avoid this bias (and make our model suitable for a DCE), we assume the lifetime license is offered for only one period at the beginning of the hunter's decision problem; if they do not purchase the lifetime license in period 0, then they will never have the chance to purchase it ever again. For a given choice h^*_{ijt}, this assumption implies

$$\ln\left(\sum_{j \in \mathscr{C}(\mathbf{H}_{it+1})} \exp\left(U_{ijt+1}\right) \right) = U_{ijt+1}.$$

Formally, we have defined each choice to lead immediately to a different absorbing state, implying that, given choice j, each subject's present value of indirect utility is known up to an expectation on ε_{ijt}. We can use this information to rewrite (5) as

$$U_{ijt} = V_{ijt} + \delta_i \left[U_{ijt+1} + \gamma \right] \tag{7}$$

Updating the time index and recursively substituting the result back into (7) over T_i periods yields

$$U_{ijt} = V_{ijt}[1 + A_i] + \Gamma_i \tag{8}$$

where $A_i = [(1 + r_i)^{T_i} - 1] / [r_i(1 + r_i)^{T_i}]$ is a standard annuity factor, $r_i = (1 - \delta_i)/\delta_i$, and $\Gamma_i = \gamma A_i$. Note that Γ_i is constant across alternatives for hunter i and hence does not affect choice probability (6).

3.2. Choice experiment design

We estimate (6) using data from a DCE contained within a mail survey. We define each license bundle as a combination of three attributes: bag limit, combination of licenses for other species, and price. Table 1 defines each attribute and its levels. The bag limit attribute takes two possible levels: one antlered deer and two antlerless deer or three antlerless deer. These levels correspond to the bag limits for the current annual deer license bundle, which allows hunters to harvest three antlerless deer or two antlerless and one antlered deer every year. The license combination attribute takes seven possible values comprising a deer license bundle plus any combination of a lifetime fishing license, lifetime hunting license,[4] and lifetime spring turkey license. These correspond to the three most popular sporting licenses sold in Indiana. Lastly, the price attribute takes seven possible values. These correspond to the present value of the cost of each license combination over 30 years at a 2.5% percent discount rate (Brookshire et al., 1983).

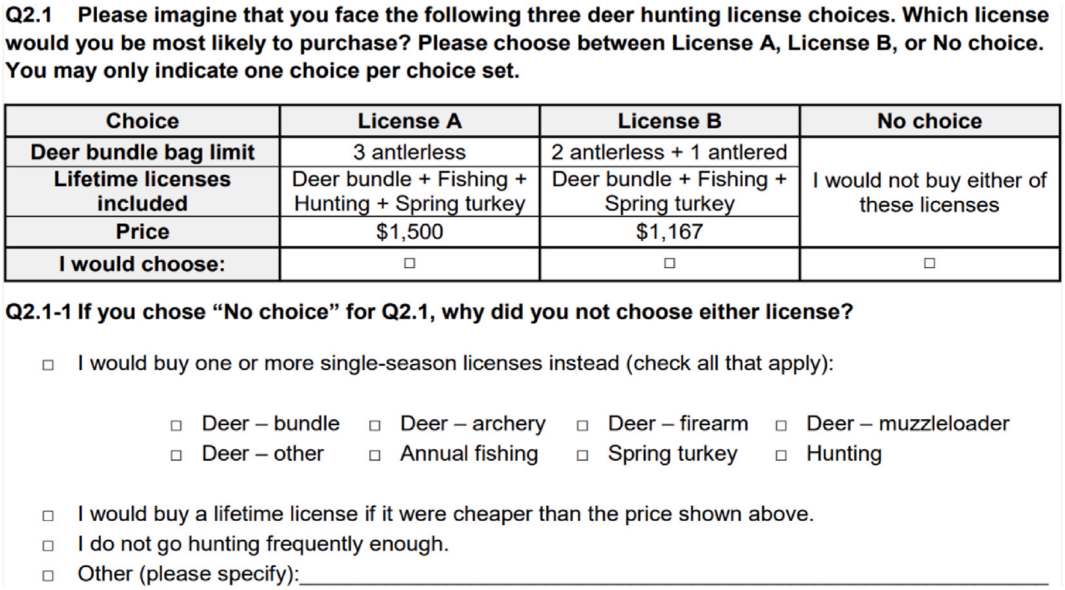
We used SAS to identify a *D*-optimal ($D = 92.22$) fractional factorial experimental design comprising five blocks of ten choice sets. Each choice set consists of two lifetime licenses comprising different combinations of the attributes in Table 1 and one *status quo* or opt-out choice, representing the option to not purchase either lifetime license. Fig. 1 shows an example of a choice set.

A follow-up question (as in Q2.1-1 in Fig. 1) was also given to the subjects who chose neither license to gather information about why they did not choose one of the given lifetime licenses. In particular, we ask subjects to report which single-season licenses they would purchase instead of the lifetime licenses. We use this information to calculate the price of the no choice, *status quo* alternative. This information forms the basis for some robustness checks, which we describe later.

[4] In Indiana, the hunting license is effectively a small game hunting license and allows harvest of sixteen species, including rabbits, squirrels, turtles, frogs, red and gray foxes, coyotes, raccoons, opossum, striped skunks, quail, pheasants, crows, doves, woodcocks, waterfowl, and migratory birds. Hunting licenses do not allow harvest of deer.

Table 1
Discrete choice experiment attributes and levels.

Attribute	Definition	Levels
Bag limit	The number and sex of deer the hunter can harvest	3 antlerless 2 antlerless +1 antlered
License combination	Other lifetime licenses included with the lifetime deer license bundle	Deer bundle Deer bundle + fishing Deer bundle + hunting Deer bundle + spring turkey Deer bundle + fishing + hunting Deer bundle + fishing + spring turkey Deer bundle + fishing + hunting + spring turkey
Price	The up-front cost of the license	\$500/\$833/\$1167/\$1500/\$1833/\$2167/\$2500



Q2.1 Please imagine that you face the following three deer hunting license choices. Which license would you be most likely to purchase? Please choose between License A, License B, or No choice. You may only indicate one choice per choice set.

Choice	License A	License B	No choice
Deer bundle bag limit	3 antlerless	2 antlerless + 1 antlered	I would not buy either of these licenses
Lifetime licenses included	Deer bundle + Fishing + Hunting + Spring turkey	Deer bundle + Fishing + Spring turkey	
Price	\$1,500	\$1,167	
I would choose:	□	□	□

Q2.1-1 If you chose "No choice" for Q2.1, why did you not choose either license?

□ I would buy one or more single-season licenses instead (check all that apply):

□ Deer – bundle □ Deer – archery □ Deer – firearm □ Deer – muzzleloader
□ Deer – other □ Annual fishing □ Spring turkey □ Hunting

□ I would buy a lifetime license if it were cheaper than the price shown above.
□ I do not go hunting frequently enough.
□ Other (please specify):____

Fig. 1. Example of choice set from mail survey.

3.3. Sampling and data collection

The DCE was embedded in a survey which comprised three parts. The first part contained questions asking about subjects' hunting experience and their opinions on Indiana deer hunting. The second part presented subjects with the DCE. The last part collected subjects' demographic information. We distributed the survey via mail and designed the survey instrument following the methods outlined in Dillman et al. (2014). Copies of the survey are available in the supporting information.

We sent the mail survey to a random sample of 2500 Indiana residents who had purchased a deer hunting license in the past five years. The survey comprised two separate mailings. The first mailing took place in mid-January 2021 and included a cover letter, the survey, and a prepaid return envelope. Reminder postcards were sent approximately 10 days after the initial mailing, followed by a second survey mailing approximately one week thereafter. We received 487 completed surveys. We removed 11 surveys with suspected protest responses. We considered these protest responses due to the presence of obviously misleading responses and/or offensive comments written in the survey. This response behavior is indicative of subjects objecting to or rejecting the premise of the survey (Boyle 2017). About 75 percent of those with protest responses are male, their average age is 58 years old, and the average income is \$69,500. The median education level is high school or equivalent. Our final sample includes 410 responses for a response rate of 16.4 percent. Table 2 compares the demographics for our sample of subjects to the population of Indiana deer hunters. We found that the percentage of male hunters or young hunters (age 18–24) from the sample hunters are statistically different from that of the population of hunters at the one percent level. Likewise, our survey oversampled poorer and wealthier hunters relative to the population.

Survey responses may be influenced by a unique feature of Indiana state law. Normally, hunters who hunt on their own land are not required to buy a deer license under what is known as a "landowner exemption." We drew our sample from a list of people who had recently purchased deer licenses, and hence ~6 percent of sample subjects have a landowner exemption. Landowner preferences—and hence their choice behavior—may be systematically different from non-landowners. For example, these individuals might buy a

Table 2
Demographics of resident hunter population and sample.

Characteristic		Population	Sample[a]
Gender			
	Male	87.2	84.63
	Female	12.69	15.37
	Other	0.11	0.00
Age			
	Less than16	0.02	–
	16–17	0.06	–
	18–24	7.43	11.22***
	25–34	21.39	24.15
	35–44	23.08	23.9
	45–54	19.34	18.29
	55–64	16.07	15.85
	65–74	8.48	5.37**
	75+	4.14	1.22***
Income			
	< $20,000	0.42	3.9***
	$20,000 - $29,999	2.53	4.63***
	$30,000 - $39,999	8.36	6.83
	$40,000 - $49,999	15.59	8.78***
	$50,000 - $74,999	47.87	20.00***
	$75,000 - $99,999	19.57	24.39**
	$100,000 - $149,999	5.10	19.02***
	$150,000 +	0.54	12.44***

[a] Superscripts ***, **, and * indicate the sample proportion is statistically different from the population proportion at the 1, 5, and 10 percent level.

lifetime deer license as a gift for a grandchild or for another hunter in the future, but not for their own personal use. We therefore drop subjects with landowner exemptions from our dataset for consistency with the choice model we develop here.

Fig. 2 shows the probability that a subject of a given age selected the *status quo* or opt-out choice during a given choice occasion, calculated from our data. This probability increases with age (albeit nonmonotonically). We would expect this to occur if the present value of hunters' utilities from the lifetime license decreases with age and remaining hunting years; hence, Fig. 2 provides evidence supporting our choice to model subject behavior as forward-looking.

4. Estimation

We now describe our procedures for estimating the choice probability (6). We write the present value of indirect utility in equation (8) as

$$U_{ijt} = \mathbf{X}_{ijt}^{'}\boldsymbol{\alpha}_i[1 + A_i] + \mu p_{ijt} + \Gamma_i, \tag{9}$$

where $\mathbf{X}_{ijt}$ is a vector of lifetime license characteristics, including an alternative-specific constant for the *status quo* alternative, and p_{ijt} is the price of license j from the DCE.[5] We abuse notation here slightly by using t to denote the choice occasion in which survey subject i chose alternative j. Our specification of U_{ijt} assumes hunters have heterogeneous preferences for deer licenses. Specifically, we let $\boldsymbol{\alpha}_i = \overline{\boldsymbol{\alpha}} + \boldsymbol{\sigma}\boldsymbol{\eta}_i$, where $\boldsymbol{\eta}_i$ is a $k \times 1$ vector of hunter-specific random shocks, assumed to be independently and standard normally distributed. This implies $\overline{\boldsymbol{\alpha}}$ is a vector of the mean of the marginal utility parameters and $\boldsymbol{\sigma}$ is a diagonal matrix with non-zero elements $\sigma_{\alpha k}$ equal to the standard deviations of the utility parameters.

Given T_i and r_i, we could estimate $\boldsymbol{\alpha}_i$ and μ using a standard random parameter logit model after multiplying the attribute data $\mathbf{X}_{ijt}$ by the annuity factor $1 + A_i$. However, we do not have information about how long subjects plan to hunt, nor did we elicit their discount rates. This is a problem because the parameters r_i and T_i are not separately identifiable in A_i. We overcome this by first setting T_i for each subject equal to the difference between their life expectancy and their reported age. We calculate life expectancy conditional

[5] We implicitly treat the *status quo* price as zero such that we could interpret the lifetime license prices respondents saw during the choice experiment as increases in expenditure relative to their *status quo*. In reality, a rational respondent should weigh the price of a lifetime license against the present value of their expected annual expenditures on the single-season licenses they buy in their *status quo* setting. As a robustness check, we calculated respondents' *status quo* expenditures from the follow-up question we described in Fig. 1 and treated this as the *status quo* price instead. We also adjusted the prices of the lifetime licenses shown to respondents to account for the present value cost of licenses they normally buy that were not included in the lifetime license. The resulting estimates fit the data worse than the models we present here, suggesting respondents focused only on the prices shown to them in the DCE.

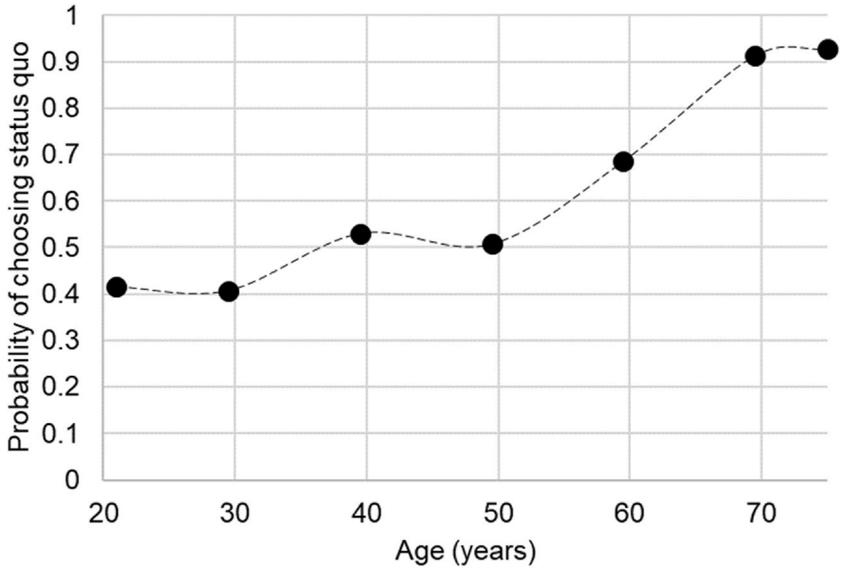


Fig. 2. Unconditional probability of choosing the *status quo* alternative by age.

Table 3
Estimated hunter utility functions models 1, 2 and 3 (n = 3955).

	Model 1: T_i = life expectancy		Model 2: T_i = max(0,65-age$_i$)		Model 3: r = 0.025	
	Estimate	SE	Estimate	SE	Estimate	SE
Mean utility parameters ($\overline{\boldsymbol{\alpha}}$)						
Status quo	−0.0120	0.0248	−0.2009	0.1704	0.0103	0.0154
Bag limit (base = 3 antlerless)						
1 antlered, 2 antlerless	0.2496**	0.1160	1.3947**	0.5863	0.1766***	0.0541
License combinations (base = deer bundle only)						
Deer bundle + fishing	0.0685**	0.0338	0.3424**	0.1690	0.0361**	0.0167
Deer bundle + hunting	0.0207	0.0216	0.0097	0.1222	0.0055	0.0159
Deer bundle + spring turkey	0.0300	0.0258	0.1020	0.1392	0.0138	0.018
Deer bundle + fishing + hunting	0.1683**	0.0784	0.9183**	0.3902	0.1082***	0.0369
Deer bundle + fishing + spring turkey	0.0889**	0.0427	0.3753**	0.1895	0.025	0.0201
Deer bundle + fishing + hunting + spring turkey	0.2175**	0.1023	1.1614**	0.4884	0.1243***	0.0395
Price	−0.0035***	0.0005	−0.0056***	0.0016	−0.0046***	0.0014
Variance of utility parameters ($\boldsymbol{\sigma}_\alpha$)						
Status quo	−0.0870	0.0594	0.7274*	0.4272	0.1142**	0.0485
Bag limit (base = 3 antlerless)						
1 antlered, 2 antlerless	−0.0695	0.0519	−0.7394*	0.3840	0.1184***	0.0457
License combinations (base = deer bundle only)						
Deer bundle + fishing	0.1213*	0.0633	0.7002*	0.3700	0.1076**	0.0418
Deer bundle + hunting	0.2168**	0.1098	1.368**	0.6176	0.1528***	0.0541
Deer bundle + spring turkey	0.1521**	0.0756	0.9609**	0.4714	0.1242**	0.0489
Deer bundle + fishing + hunting	0.1251*	0.0732	0.6649*	0.3843	0.1186***	0.0444
Deer bundle + fishing + spring turkey	0.2555**	0.1298	1.5715**	0.7129	0.2231***	0.0746
Deer bundle + fishing + hunting + spring turkey	0.2110*	0.1123	1.1089**	0.5265	0.1781***	0.0654
Discount rate parameters						
Constant	−3.4892***	0.6850	−1.698***	0.3588	–	–
Age	0.0382***	0.0071	0.0294***	0.0092	–	–
Income	−5.0E-6**	2.3E-6	−3.5E-6	2.2E-6	–	–
Male	−0.1411	0.2035	−0.1088	0.2187	–	–
σ_r	1.0943***	0.3076	1.1664***	0.1939	–	–
Akaike Information Criterion	6185		6148		6282	

[a] Superscripts ***, **, and * indicate estimates are significant at the 1, 5, and 10 percent level, respectively.
[b] Standard errors are clustered at the individual level. There are 410 unique individuals in our dataset.

on age using county-level estimates from Arias et al. (2018). We refer to this as "Model 1." An individual's conditional life expectancy likely overestimates their actual time horizon as deer hunting can be physically quite rigorous. Huck and Winkler (2008) find that participation among Wisconsin deer hunters declines precipitously after age 65. Hence, we estimate a separate model, referred to as "Model 2," in which we set T_i equal to the difference between 65 and each subject's age or zero, whichever is greatest.

Given T_i, we then assume r_i is randomly distributed across the population, with the distribution being a function of subject's demographic characteristics. Specifically, for both Models 1 and 2, we assume $r_i = e^{\mathbf{Z}_i'\boldsymbol{\theta}+\sigma_r\nu_i}$, where $\mathbf{Z}_i$ is a vector including a constant along with respondent i's age, income, and a binary variable equal to one if the subject is male, ν_i is an i.i.d. standard normal shock (so that r_i is lognormally distributed), and $\boldsymbol{\theta}$ and σ_r are parameters. Identification of $[\boldsymbol{\theta}, \sigma_r]$ and $[\overline{\boldsymbol{\alpha}}, \boldsymbol{\sigma}_\alpha]$ in this case is due to the nonlinearity of the normal distribution.

An alternative estimation strategy is to simply fix $r_i = r\,\forall i$ at some reasonable value (Scott 2013; Reeling et al., 2020). This is a more common strategy in estimating dynamic discrete choice models as r_i is often weakly identified due to collinearity issues (Hicks and Schnier 2006). Our final model, which we refer to as "Model 3," sets $r = 0.025$ (Brookshire et al., 1983) and T_i equal to each hunter's life expectancy, as in Model 1.

Let $\boldsymbol{\Omega}$ be a vector that collects all of the random variables (such that $\boldsymbol{\Omega} = [\boldsymbol{\alpha}, r]$ for Models 1 and 2 and $\boldsymbol{\Omega} = [\boldsymbol{\alpha}]$ for Model 3) and $\boldsymbol{\beta}$ be the vector of distribution parameters to be estimated. The joint density is $f(\boldsymbol{\Omega}|\boldsymbol{\beta})$. The probability hunter i chooses alternative j takes the standard random parameters logit form,

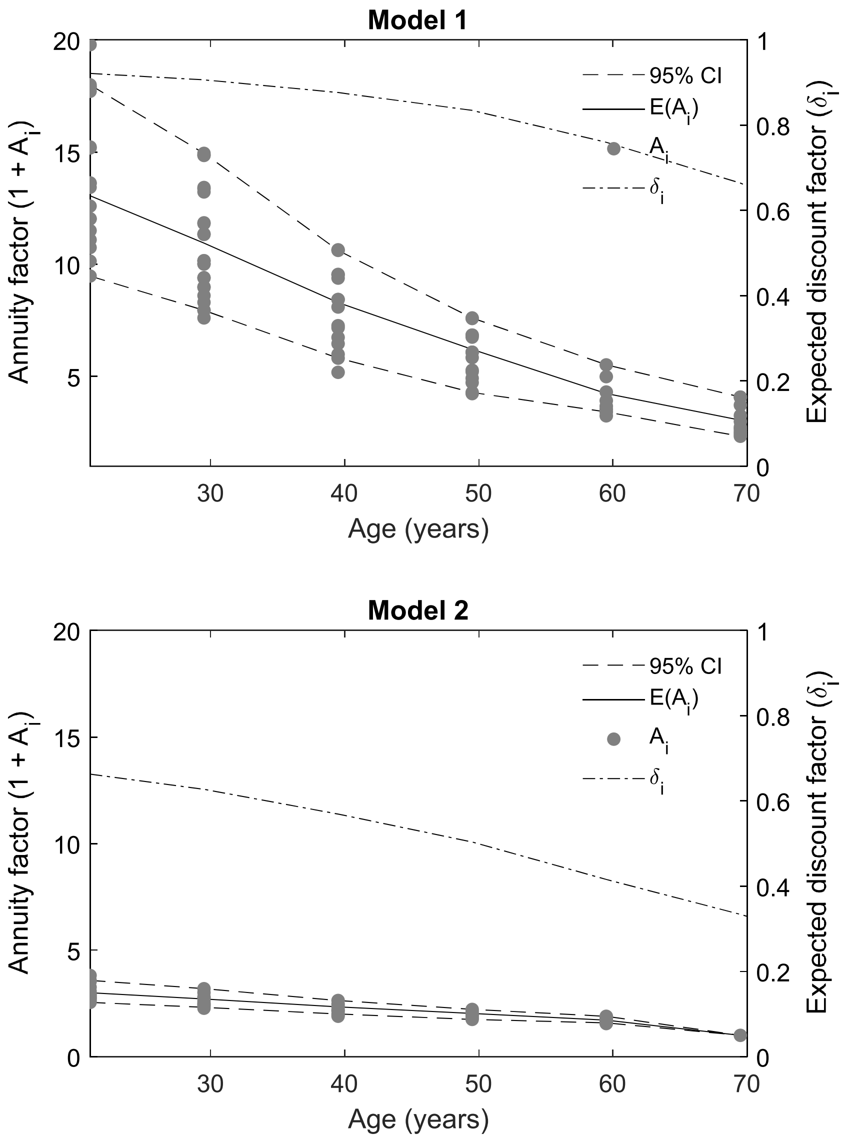


Fig. 3. Subjects' expected annuity and discount factors, Models 1 and 2.

$$\int \Pr\left(U_{ijt}(\mathbf{\Omega}) + \varepsilon_{ijt} > U_{ij't}(\mathbf{\Omega}) + \varepsilon_{ij't} \forall j' \neq j\right) f(\mathbf{\Omega}|\boldsymbol{\beta}) d\mathbf{\Omega} = \int \frac{e^{U_{ijt}}}{\sum_{j'} e^{U_{ij't}}} f(\mathbf{\Omega}|\boldsymbol{\beta}) d\mathbf{\Omega} = \int \pi_{ijt}(\mathbf{\Omega}) f(\mathbf{\Omega}|\boldsymbol{\beta}) d\mathbf{\Omega}. \tag{10}$$

We estimate the choice probability (10) via simulation in MATLAB following Train (2009). Our code is available in the online supplemental appendix.

5. Results

Table 3 shows estimation results for Models 1–3 with standard errors clustered at the individual level. All utility function parameters have the expected signs and are largely consistent across models. The coefficient for the *status quo* alternative-specific constant is negative for Models 1 and 2, indicating that hunters prefer purchasing the lifetime license instead of their *status quo* license choice, all else equal. This estimate is positive for Model 3, but in no case is it significantly different from zero. The positive mean coefficient on the 1 antlered, 2 antlerless deer attribute reveals that hunters also prefer licenses that allow them to harvest an antlered deer to one that only allows harvest of antlerless deer. The positive coefficients on the license combinations binary variables indicate that combining licenses for other species with a deer license gives hunters greater utility, although the magnitude of this effect differs by species. The mean coefficient of the deer, fishing, hunting, and spring turkey license combination has the greatest magnitude among all license combinations. The estimated standard deviations of the utility function parameters, $\boldsymbol{\sigma}_\alpha$, are all significant except for the *status quo* constant and the bag limit binary variable in Model 1, implying preference heterogeneity among subjects. The estimates from Model 3 are marginally more precise than those from Models 1 and 2 due to inherent collinearity issues in those models. However, Model 3 has a larger AIC than either Models 1 or 2 and hence fits the data worse.

Models 1 and 2 also estimate subjects' discount rates. All of the estimated parameters are statistically significant except for that of the male binary variable in both models and the income variable in Model 2. Intuitively, we find that older subjects tend to have larger discount rates, all else equal. Fig. 3 shows the annuity factors calculated for each subject in models 1 and 2, where the solid black line shows the mean of these annuity factors and the dotted lines show the 95% confidence intervals.[6] These calculated annuity factors imply that the oldest hunters place very little weight on future hunting opportunities, and hence would be less likely to purchase a relatively expensive lifetime license relative to their *status quo* license bundle. This matches the intuition derived from Fig. 2. Notably, the annuity factors calculated in Model 2 are smaller and converge to 1 (such that hunters are effectively myopic) by age 65. This reflects estimated discount factors that are smaller and time horizons that are shorter than those in Model 1. Overall, the magnitudes of the discount factors in Model 1 appear more reasonable (dot-dash line, right axes, Fig. 3). Hence, we will restrict attention to this model moving forward, despite the slightly worse fit measured by the Akaike Information Criterion (AIC; Table 3).

Models 1–3 directly account for subject's forward-looking behavior and were derived in agreement with our dynamic discrete choice model. As we have argued, though, we do not need to estimate a dynamic model as long as our choice experiment is framed such that any choice drives subjects into one or more absorbing states. To see this, note that we could alternatively estimate subjects' utility functions as

$$U_{ijt} = \mathbf{X}'_{ijt}\widetilde{\boldsymbol{\alpha}}_i + \widetilde{\mu} p_{ijt} + \Gamma_i. \tag{11}$$

In the extreme case that $A_i = A \ \forall i$, and these values are known, we could exactly recover the dynamic model parameters in (9) by estimating utility as in (11) and dividing the resulting estimates by $[1 + A]$.[7] Even if subjects' annuity factors are heterogeneous, as in Model 3, we could recover the dynamic model parameters by (i) calculating the expected individual-specific parameters conditional on their observed choices, as in Train (2009),

$$E(\overline{\boldsymbol{\alpha}}_i) = \frac{\int \boldsymbol{\alpha} \cdot P(h_i|\mathbf{X}_i, \boldsymbol{\alpha}) f(\boldsymbol{\alpha}|\boldsymbol{\beta}) d\boldsymbol{\alpha}}{\int P(h_i|\mathbf{X}_i, \boldsymbol{\alpha}) f(\boldsymbol{\alpha}|\boldsymbol{\beta}) d\boldsymbol{\alpha}},$$

where $P(h_i|\mathbf{X}_i, \boldsymbol{\alpha}) = \prod_t \left(e^{U_{ijt}} / \sum_{j'} e^{U_{ij't}} \right)$, and then (ii) regressing these on the calculated annuity factor for each individual (Bir et al. 2019, 2020; Lai et al., 2020). Note that neither of these approaches will eliminate potential bias in the case that choices do not lead to absorbing states.

[6] The data are clumped together at distinct ages because respondents only indicated the ranges in which their ages fall (18–24, 25–34, etc.).

[7] To see this most clearly, we follow Waldman (2000) and consider a simple setting involving a model with two alternatives, $j = 1, 2$, each of which has a single, scalar attribute x_j. Assume preferences are homogeneous and take the form $V_{ij} = \beta x_j + \varepsilon_{ij}$, where ε_{ij} is a type-1 extreme valued shock as before. Let N_1 and N_2 be the number of individuals who choose alternatives 1 and 2. We can then write the likelihood function as $L = N_1 \ln(\pi_1) + N_2 \ln(\pi_2)$, where $\pi_j = e^{V_{ij}} / (e^{V_{i1}} + e^{V_{i2}})$ is the standard conditional logit choice probability. The maximum likelihood estimate of β is expressible in closed form as $\widetilde{\beta} = \frac{\ln(N_1/N_2)}{x_1 - x_2}$. Now let $V_{ij} = \beta x_j A + \varepsilon_{ij}$, where A is some known constant analogous to the annuity factor our dynamic model. The corresponding estimates are then simply $\widetilde{\beta}/(1 + A)$ such that the ratio between the dynamic and myopic estimates is $1 + A$.

We use our estimated model to calculate the price of the lifetime license that maximizes IDNR funds for wildlife management. We assume that IDNR offers hunters only one type of lifetime license at a time alongside the *status quo*, single-season license offerings. Hunters then make a choice: they either (i) buy the offered lifetime license j or (ii) do not buy it and instead choose their *status quo* alternative for the rest of their hunting careers. Formally, we choose the lifetime license price p_j to maximize expected mean revenues per hunter,

$$\max_{p_j} \frac{1}{N} \sum_i \left[\int \left(p_j \pi_{ij}(\boldsymbol{\Omega}) + p_{i0} \left[1 - \pi_{ij}(\boldsymbol{\Omega}) \right] \right) f(\boldsymbol{\Omega}|\boldsymbol{\beta}) d\boldsymbol{\Omega} \right],$$

where N is the number of hunters, $\pi_{ij}(\boldsymbol{\Omega})$ is the probability hunter i chooses to buy the offered lifetime license j, calculated from (6), and $p_{i0} = p_{i0}[1 + A_i]$ is the present value of expenditure on the *status quo* license bundle. The value of the parameter p_{i0} varies by individual and represents the total cost of all single-season licenses individual i typically purchases. We collected this information in our survey, but only for individuals who opted not to purchase one of the proposed lifetime licenses at least once. Instead of using this data, we therefore collected information on typical license purchases for every registered hunter in the IDNR license sales database. We consider each hunter to typically purchase a given license type (either a deer bundle, fishing license, hunting license, or spring turkey license) if they purchased the license at least twice in the past three years, then calculate $p_{i0}\ \forall i$ as the sum of each hunter's typical purchases. Table 4 shows the expected revenue-maximizing prices of each lifetime license, which ranges from $2752 for a license that just includes a lifetime deer bundle to $4205 for a license that includes a lifetime deer bundle and lifetime spring turkey, hunting, and fishing licenses. These numbers seem reasonable. When Indiana last offered lifetime comprehensive hunting licenses (which included licenses to harvest all legal species in the state), their prices were set by law to 60 times the single-season rate (IC 14-22-12-7 (2011)). For comparison, the revenue-maximizing prices for the lifetime licenses here are 34–42 times the current price of their single-season counterparts.

6. Conclusion

Sales of deer licenses in Indiana have been declining for a decade, leading to a lack of funding for wildlife management at the IDNR. A lifetime deer license is being considered to increase agency funds. We estimate a discrete choice model based on choice experiment data to estimate hunter utility from different lifetime license offerings. We also estimate the license price which maximizes IDNR revenue.

Hunters are highly likely to be forward-looking when evaluating whether to purchase a lifetime license. In contrast to prior studies which estimate choice models for durable goods using DCEs underpinned by a standard, static behavioral model, we explicitly model individuals' forward-looking behavior. We then use our behavioral model to inform the design of a dynamic DCE that can capture subjects' forward-looking behavior in the context of a one-time survey. We are not aware of prior studies that do this, although we argue that explicit consideration of dynamics in behavior models can be important for avoiding bias in the estimation of preference parameters.

The key to our approach is being able to craft a believable DCE in which any possible decision sends subjects into an absorbing state such that their continuation value—that is, their future utility conditional on a given choice—is known up to an expectation on any state variables and shocks. In our study, hunters who chose to purchase a hypothetical lifetime license never needed to purchase licenses for the covered species ever again. The take-it-or-leave-it nature of the license offer meant that hunters who passed on the license would never have the opportunity to buy another one and would be stuck purchasing their *status quo* license bundles. The nature of the offer is admittedly extreme, but the IDNR has offered—and then suddenly withdrawn—the sale of lifetime hunting and fishing licenses in the past. Whether our approach can be believably generalized to other settings involving long-lived durable goods will depend on the specific nature of the decision problem being simulated.

Consideration must also be given to whether DCEs are suitable for specific long-lived goods. The bulk of the DCE literature tends to focus on consumers' decisions over nondurable goods that comprise a small share of their budget and that they purchase frequently and hence are relatively familiar with, like food products (Livingstone et al., 2021; Staples et al., 2020) or transportation mode choices for single trips (Koo et al., 2018). We believe a DCE is appropriate for estimating preferences over lifetime licenses because our sample of subjects comprises hunters who have otherwise had to make hunting license purchases annually. Further, the highest license prices we showed subjects amounts to less than 3% of their average income.

Empirically, our work is the first study to estimate the value of lifetime deer hunting licenses. Understanding demand for lifetime

Table 4
Calculated expected revenue-maximizing lifetime license prices.

Lifetime License	Price ($)
Deer bundle only	$2752
Deer bundle + fishing	$3203
Deer bundle + hunting	$3478
Deer bundle + spring turkey	$3234
Deer bundle + fishing + hunting	$3701
Deer bundle + fishing + spring turkey	$3788
Deer bundle + fishing + hunting + spring turkey	$4205

licenses is important because at least 32 states in the U.S have offered lifetime fishing and hunting licenses in the past (Frisman 2005). The sale of lifetime licenses has important consequences for wildlife management funding. Under the Pittman-Robertson Act, the federal government distributes funds earned from taxes on firearm and ammunition sales to state wildlife management agencies in accordance with land area and the number of annual license sales. Because lifetime licenses are sold once and are valid for the rest of the buyer's life, the government will distribute funds for each lifetime license sold annually over the license holder's statistical life expectancy (Frisman 2005). This implies that a state can continue to earn Pittman-Robertson funds for lifetime license holders who stop participating in hunting—and who would therefore stop earning Pittman-Robertson funds if only annual hunting licenses were sold. By improving our understanding of demand for lifetime licenses, this work can help increase the stability of state-level funding to support wildlife management.

Role of the funding source

This project was funded by a Wildlife Restoration Grant (F20AF10970, W-52-R-01) in cooperation with the Indiana Department of Natural Resources, Division of Fish & Wildlife, and the U.S. Fish & Wildlife Service Wildlife Restoration Grant Program. The IDNR has not reviewed or commented on this paper.

Author statement

Yusun Kim: data curation, formal analysis, investigation, methodology, validation, visualization, writing – original draft, writing – review & editing. **Carson Reeling:** Conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, project administration, resources, software, supervision, validation, visualization, writing – review & editing. **Nicole J.O. Widmar:** Conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, supervision, validation, visualization, writing – review & editing. **John G. Lee:** Conceptualization, data curation, formal analysis, funding acquisition, investigation, methodology, supervision, validation, visualization, writing – review & editing.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: Carson Reeling reports financial support was provided by Indiana Department of Natural Resources.

Data availability

Data will be made available on request.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jocm.2023.100414.

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