

Research Article

# Collective Factors Reinforce Individual Contributions to Human-Wildlife Coexistence

HOLLY K. NESBITT<sup>1</sup>,<sup>1</sup> University of Montana, 32 Campus Drive, Missoula, MT 59812, USA

ALEXANDER L. METCALF<sup>1</sup>, University of Montana, 32 Campus Drive, Missoula, MT 59812, USA

ALICE A. LUBECK, University of Montana, 32 Campus Drive, Missoula, MT 59812, USA

ELIZABETH COVELLI METCALF, University of Montana, 32 Campus Drive, Missoula, MT 59812, USA

CRYSTAL BECKMAN, Montana Department of Natural Resources and Conservation, 2705 Spurgin Road, Missoula, MT 59804, USA

ADA P. SMITH<sup>1</sup>, University of Montana, 32 Campus Drive, Missoula, MT 59812, USA

TINA M. CUMMINS<sup>1</sup>, University of Montana, 32 Campus Drive, Missoula, MT 59812, USA

**ABSTRACT** Conserving large carnivores while keeping people safe depends on finding means for peaceful coexistence. Although large carnivore populations are generally declining globally, some populations are increasing, causing greater overlap with humans and increasing potential for conflict. One method of reducing conflict with large carnivores is to secure attractants like garbage and livestock. This method is effective when implemented; however, implementation requires a change in human behavior. Human-wildlife interaction is a public good collective action problem where solutions require contributions from many and individual actions have effects on others. We used the collective interest model to investigate how individual and collective factors work in concert to influence landowner attractant securing behavior in Montana, USA, in black (*Ursus americanus*) and grizzly bear (*U. arctos*) range. We used data from a mail-back survey to develop logistic regression models testing the relative effects of collective and individual factors on landowners' attractant securing behaviors. The most important factor was whether individuals had spoken to a wildlife professional, a reflection of social coordination and pressure. Other collective factors (e.g., social norms [i.e., expectations and behaviors of peers] and the existence of discussion networks [i.e., how much social influence an individual has]) were equally important as individual factors (e.g., beliefs, age, gender) for influencing attractant securing behavior among Montana landowners. This research suggests pathways for wildlife managers and outreach coordinators to increase attractant securing behavior by emphasizing collective factors, such as social norms, rather than appealing exclusively to individual factors, such as risk perception of large carnivores. Furthermore, wildlife agencies would be justified in increasing their efforts to connect with landowners in person and to connect with members of the public who play an important role in discussion networks. This research demonstrates that, even on private lands, collective interests may be a missing and important piece of the puzzle for encouraging voluntary attractant securing behavior and improving wildlife-human coexistence. © 2021 The Wildlife Society.

**KEY WORDS** attractants, black bears, carnivores, collective action, grizzly bears, human-wildlife conflict, social norms.

Despite some confusion over its exact definition (Bhatia et al. 2020, Knox et al. 2021), coexistence with carnivores is an increasingly common goal for wildlife agencies, especially in areas where large carnivore populations are increasing and stakeholders are attempting to mitigate their effects on people (Frank et al. 2019). Although large carnivores are of global conservation concern and most populations are declining around the world (Ripple et al. 2014), there are a few instances where populations are growing or ranges are

expanding. In these areas, at least partly because of increased human-carnivore overlap, reported interactions and conflicts (i.e., negative interactions) have increased, such as with wolves (*Canis lupus*) in the United States (Treves et al. 2002) and Europe (Salvatori and Linnell 2005), brown or grizzly bears (*Ursus arctos*) in Scandinavia (Støen et al. 2018) and Canada (Morehouse and Boyce 2017), Asiatic black bears (*U. thibetanus*) in Japan (Honda et al. 2009b), cougars (*Puma concolor*) in North America (Beier 1991, Halffpenny et al. 1991), and American black bears (*U. americanus*) in North America (Baruch-Mordo et al. 2008, Colorado Parks and Wildlife 2015, Morehouse and Boyce 2017). Black and grizzly bear populations are

Received: 15 July 2020; Accepted: 18 March 2021

<sup>1</sup>E-mail: nesbitt.holly@gmail.com

expanding (Garshelis et al. 2016, Interagency Grizzly Bear Committee 2020), interactions with humans are increasing (Morehouse and Boyce 2017), and debates regarding grizzly bear listing status in the contiguous United States under the Endangered Species Act (ESA) are escalating (Mott and Burnham 2019). Conflicts such as these pose a substantial challenge for the continued recovery of large carnivores globally. Efforts to reduce negative human-wildlife interactions are generally selected from a suite of measures that strive to be consistent with recovery and conservation goals (Treves and Karanth 2003) and can include aversive conditioning, translocation, or euthanasia of animals; monetary compensation or incentives paid to victims of carnivore effects; and modifications to human behavior (Sillero-Zubiri et al. 2007, Krafte Holland et al. 2018).

Conflict reduction measures seeking to modify human behavior to reduce the likelihood of negative human-wildlife interactions can benefit from social science insights and experimental evaluations of human behavioral interventions (Lischka et al. 2018). Human behaviors that can help reduce negative interactions with wildlife include animal husbandry practices, such as maintaining small herds and keeping herds closer to people, and securing attractants, such as removing food sources or establishing physical barriers (Sillero-Zubiri et al. 2007, Krafte Holland et al. 2018). Efforts to reduce the likelihood of human interactions with carnivores by securing attractants are effective in agent-based modeling exercises (Marley et al. 2017, 2019) and practical applications (Bradley and Pletscher 2005, Honda et al. 2009a, Wilson et al. 2018), yet most effectiveness studies assume that human behavior is easy to change (Dietsch et al. 2018). Assumptions such as these lead practitioners to believe that they simply need to educate the public for them to adopt desired behaviors; however, human behavior is far more complex and behavior change is far more challenging (Heberlein 2012, Gore et al. 2016). For example, attractant securing behaviors may be influenced by factors intrinsic to each individual person, such as past experiences with carnivores (Pienaar et al. 2015), attitude towards the behavior (Martin and McCurdy 2009, Willcox et al. 2012), and perceived risk (Eklund 2019). Although education and outreach can help improve people's knowledge on how to secure carnivore attractants properly, limiting factors such as time and money may hinder uptake of attractant securing behavior regardless of an individual's level of understanding or desire (Pienaar et al. 2015, Dietsch et al. 2018). Although a few studies have investigated how these individual factors influence uptake of attractant securing behavior, the effects of social pressures (i.e., collective factors) are not well understood and may prove useful for efforts to inspire adoption of these behaviors.

Individual decisions by landowners and social dynamics among landowners make coexisting with wildlife a collective social experience. For example, landowners who protect themselves from negative carnivore interaction by installing electric fences may transfer risk to neighbors (Asheim and Mysterud 2005, Osipova et al. 2018), whereas landowners

who fail to secure attractants may elevate risk for themselves and neighbors alike. Furthermore, social-psychological dynamics may compound the collective nature of human-wildlife coexistence. For example, an individual's decision to secure carnivore attractants may be influenced by the behaviors and expectations of peers (i.e., social norms; Martin and McCurdy 2009, Willcox et al. 2012, Young 2018), even more so than their own attitudes and perceived behavioral controls (Sakurai et al. 2015) or emotions (Eklund 2019). There is a large body of evidence reporting that social norms substantially influence human behavior in a wide range of contexts, including wildlife management (Zinn et al. 1998, Campbell and Mackay 2003, Marchini and Macdonald 2012, Ceaușu et al. 2019). Additionally, there is a small but growing effort to understand the role of social norms on carnivore attractant securing behaviors (Martin and McCurdy 2009, Willcox et al. 2012, Sakurai et al. 2015, Young 2018, Eklund 2019).

Despite increasing attention to normative influences on human behavior and the collective behaviors required to successfully mitigate human-wildlife conflict, the mechanisms by which collective action influences human-wildlife coexistence remain unclear. In its most basic terms, collective action problems arise when the efforts of  $\geq 2$  actors are required to accomplish an outcome (Ostrom 1998, Sandler 2015). In common pool resource collective action problems, solutions require restraint to prevent resource depletion, as opposed to public good collective action problems, which generally require contributions from actors to maintain or produce the public good (Graham et al. 2019, Niemiec et al. 2020). Required contributions to collective action solutions for the public good (e.g., securing bear attractants) can be facilitated or constrained by individual and collective factors. Although individual factors, such as age, values, education, gender, and abilities, are intrinsic, collective factors arise from the collective character of the context or problem, such as an understanding of interactions across scales and boundaries, beliefs about community expectations, and confidence in the group's ability to accomplish goals (Ostrom 1990, Chong 1991, Finkel and Muller 1998). These collective factors can be a result of external forces (e.g., formal laws or sanctions or informal social sanctions) or internal forces (e.g., wanting to be neighborly), and are often interrelated. Although individuals may pursue self-interested actions that do not further the best interests of the group, individuals may change their behavior to reciprocate the actions of others, particularly if they trust each other, and to protect their reputation to meet perceived community expectations based on normative beliefs (Ostrom 1998). Collective action theory has been helpful for better understanding natural resource issues, such as managing weeds on private land (Yung et al. 2015) and wildlife (Wagner et al. 2007), illuminating the importance of social capital (e.g., trust, reciprocity, shared norms or values, and social networks) in forming voluntary associations (Wagner et al. 2007), and influencing perceptions of risk (Carter et al. 2020). These factors can either facilitate or constrain cooperation toward

mutually beneficial outcomes. Wildlife managers have reported use in collective action theory in Florida, USA, where human behavior (i.e., securing bear attractants) has been related to whether a person believes their behavior will influence the collective goal of reduced human-wildlife conflict (Pienaar et al. 2015). Expanded adoption of a collective action frame may continue to prove useful given the collective interest in securing wildlife attractants, a voluntary behavior likely influenced by social norms, trust, and other collective factors.

One way to examine the relative effects of individual and collective factors on human behavior is through the collective interest model (Finkel et al. 1989). The collective interest model has been used to explain why individuals engage in collective political activism (Finkel et al. 1989, Finkel and Muller 1998), global warming activism (Lubell et al. 2007), shared housing (Yau 2011), and weed control behaviors (Niemiec et al. 2016, Lubeck et al. 2019). For example, Lubell et al. (2007) examined the relative importance of individual and collective factors in promoting different kinds of global warming activism among people. They reported that collective factors such as perceptions of community reciprocity, perceptions of government official competence, evidence of political discussion in social networks, and level of engagement in community activities were significant predictors of global warming activism. Niemiec et al. (2016) used the collective interest model to understand factors influencing private landowner's engagement with weed control behaviors in Hawaii, USA, finding that collective factors like injunctive norms (i.e., perceived expectations from others) and community reciprocity were among the most significant factors influencing landowner behavior to control weeds—more significant than individual risk perception. In a similar study in Montana, USA, Lubeck et al. (2019) reported that weed control behaviors were significantly predicted by collective factors like injunctive norms and a belief in the cross-boundary nature of the problem. To our knowledge, this model has not been applied in the context of wildlife management but may help clarify the relative importance of individual and collective factors affecting uptake of actions that might mitigate human-wildlife conflict.

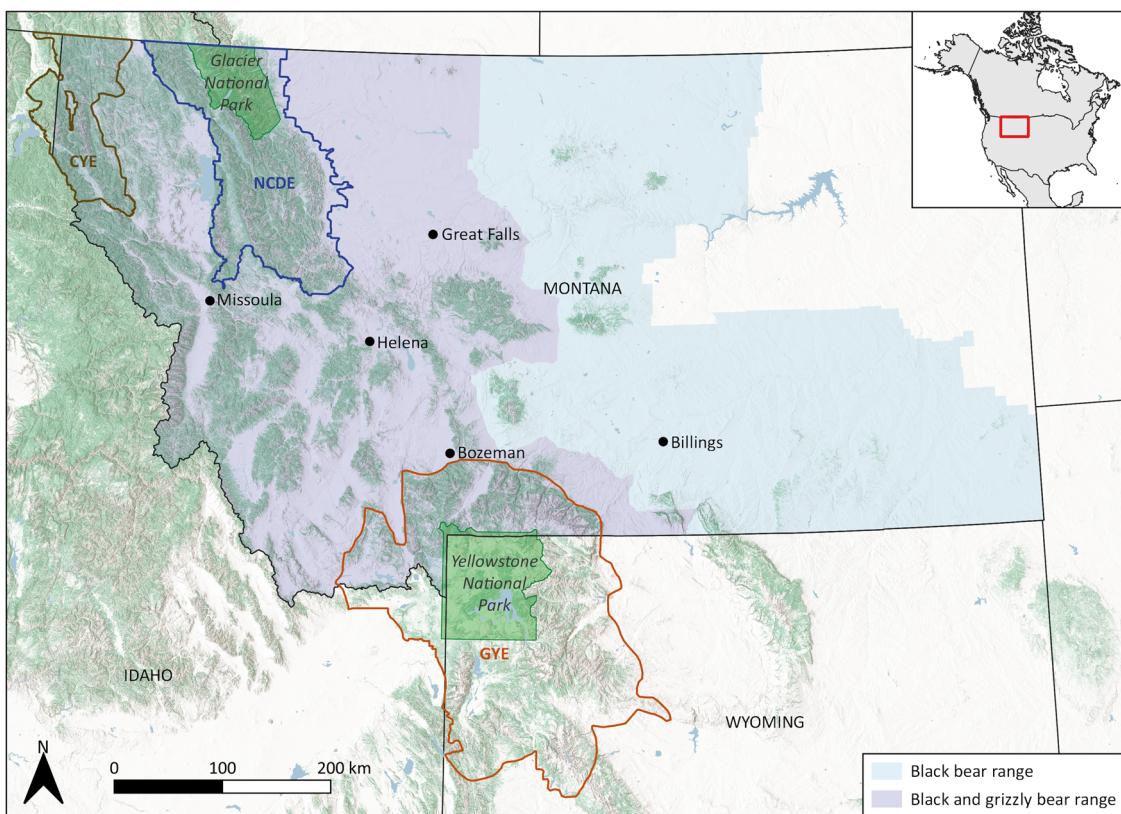
We investigated the relative importance of multiple collective factors on landowners' behaviors to secure bear attractants in Montana. We focused specifically on securing items that would attract black or grizzly bears. We applied the collective interest model to test how individual and collective factors relate to different bear attractant securing behaviors. We hypothesized that mitigating the risk of bear-human interactions on private lands is a collective action problem because, holding individual factors constant, collective factors would explain significant additional variation in individual landowner attractant securing behaviors.

## STUDY AREA

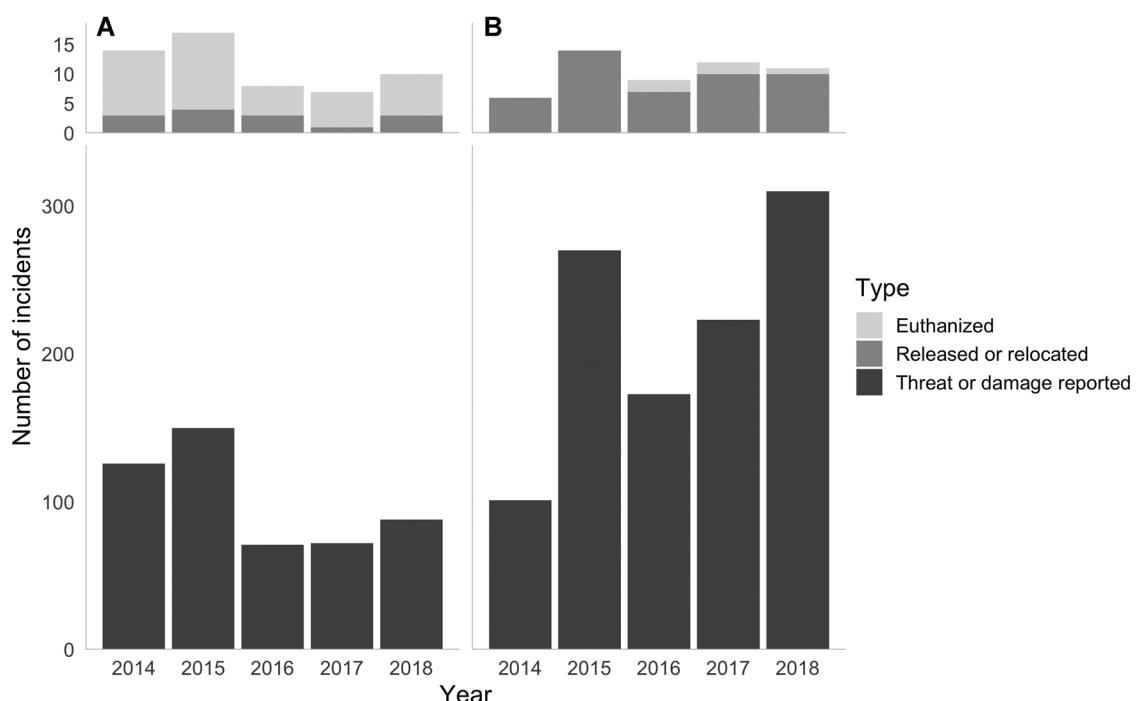
We conducted this study in Montana (380,000 km<sup>2</sup>) in 2018. Elevations in Montana range from 557 m to 3,900 m. Mountainous forested landscapes occur in the west, with

common tree species including Douglas-fir (*Pseudotsuga menziesii*), Engelmann spruce (*Picea engelmannii*), lodgepole (*Pinus contorta*) and ponderosa pines (*P. ponderosa*), quaking aspen (*Populus tremuloides*), western larch (*Larix occidentalis*), and western red cedar (*Thuja plicata*). Grass and shrub-dominated plains occur in the east, with common species including western wheatgrass (*Pascopyrum smithii*), blue grama (*Bouteloua gracilis*), rough (*Festuca campestris*) and Idaho fescue (*F. idahoensis*), and big sagebrush (*Artemesia tridentata wyomingensis*). In Montana, there are several large carnivore species, including gray wolves, mountain lions, coyotes (*C. latrans*), and bobcats (*Lynx rufus*), and ungulates, including mule deer (*Odocoileus hemionus*), pronghorn (*Antilocapra americana*), and elk (*Cervus canadensis*). There are four seasons (spring is Mar–May, summer is Jun–Aug, fall is Sep–Nov, and winter is Dec–Feb). Climate varies considerably across the state: the west is characterized by a northern Pacific coastal climate and the east by a semi-arid continental climate (Weather Atlas 2021). Average January lows range from  $-17$  to  $-5^{\circ}\text{C}$  and July highs range from  $24$  to  $31^{\circ}\text{C}$  across the state (Current Results 2021). Annual total precipitation ranges from 177.8 mm in the southern lowlands to 889 mm in the northwest mountains (Frankson et al. 2017). Dominant land uses include forestry, agriculture, and recreation. Montana has a population of just over 1 million people and a population density of 2.8 people/km<sup>2</sup> (World Population Review 2020).

Montana is home to American black and grizzly bears, the latter of which are protected by the ESA although their populations and ranges have recently expanded in certain parts of the state (Fig. 1). The Montana Department of Fish, Wildlife, & Parks (FWP) manages wildlife in the state, working in conjunction with the United States Fish and Wildlife Service for species listed under the ESA. Black bear populations are most dense in forested areas (FWP 2020), with the population most recently estimated at 13,307 individuals across the state (Mace and Chilton-Radandt 2011). Grizzly bear populations are most dense in the Northern Continental Divide (Kendall et al. 2019), Greater Yellowstone (Bjornlie et al. 2014), and Cabinet-Yaak Ecosystems (Kendall et al. 2016) with 1,000, 700, and 55–60 estimated individuals, respectively (Interagency Grizzly Bear Committee 2020). In Montana, 60% of the land base is privately owned (United States Geological Survey 2018); consequently, interactions between people and bears depend largely on individual landowner behaviors. As a conservative estimate, FWP spends approximately \$2–2.5 million/year on programs to manage black and grizzly bears, including those that encourage bear-friendly behavior among landowners and outdoor recreationists (J. A. Gude, FWP, personal communication). The United States Department of Agriculture (USDA) Wildlife Services branch manages most conflicts with wildlife in Montana. From 2014 to 2018, Wildlife Services reported 507 and 1,077 incidents with black and grizzly bears, respectively, largely due to threats or damage to livestock. They released or relocated 14 black and 47 grizzly bears,



**Figure 1.** Generalized black and grizzly bear ranges in Montana, USA, 2018 (FWP 2018). CYE = Cabinet-Yaak Ecosystem, NCDE = Northern Continental Divide Ecosystem, GYE = Greater Yellowstone Ecosystem.



**Figure 2.** Number of A) American black and B) grizzly bear incidents in Montana, USA, as reported by United States Department of Agriculture Wildlife Services branch, 2014–2018 (USDA 2019).

and euthanized 42 black and 5 grizzly bears (Fig. 2; USDA 2019).

## METHODS

### Data Collection

We collected data for this study using a mail-back questionnaire administered in 2018 to Montana private landowners (Appendix A, available online in Supporting Information). We co-developed the survey with several natural resource agencies to address 3 natural resource management issues, including wildfire preparedness, invasive weed control, and securing bear attractants. We defined our sampling frame to include private landowners who owned between 0.2 ha and 2,500 ha in unincorporated areas. We selected this population because they were of particular interest to our partners involved in natural resource outreach and education campaigns. We initially stratified the sample into 3 different regions, west to east, with 1,500 landowners sampled in each region (4,500 statewide) using the publicly available Montana cadastral dataset (Montana State Library 2019); after we removed duplicates and incorrect addresses, our initial sample size was 4,424. Eleven people pre-tested the questionnaire: 4 university graduate students and faculty, 4 state natural resource agency employees, and 3 extension professionals. To administer the survey, we used a cover letter announcing the forthcoming survey, questionnaire, reminder postcard, and 2 replacement questionnaires to non-respondents, each mailed approximately 2 weeks apart (Dillman et al. 2014). The University of Montana's Institutional Review Board approved all research methods (protocol 22-17).

### Conceptual Model

We used the collective interest model to determine the relative effects of collective and individual factors on whether landowners secured bear attractants on their property. The model posits that the expected utility of engaging in a collective action for an individual ( $E[\mathcal{A}]$ ) will be a function of the value that an individual assigns to the public good produced by the action ( $V$ ), the perceived probability that the individual's actions will contribute to producing the public good (i.e., personal efficacy [ $p_i$ ]), the perceived probability that the group's actions will contribute to producing the public good (i.e., group efficacy [ $p_g$ ]), and the benefits ( $B$ ) and costs ( $C$ ), defined broadly, of engaging in the action (Finkel et al. 1989), where:

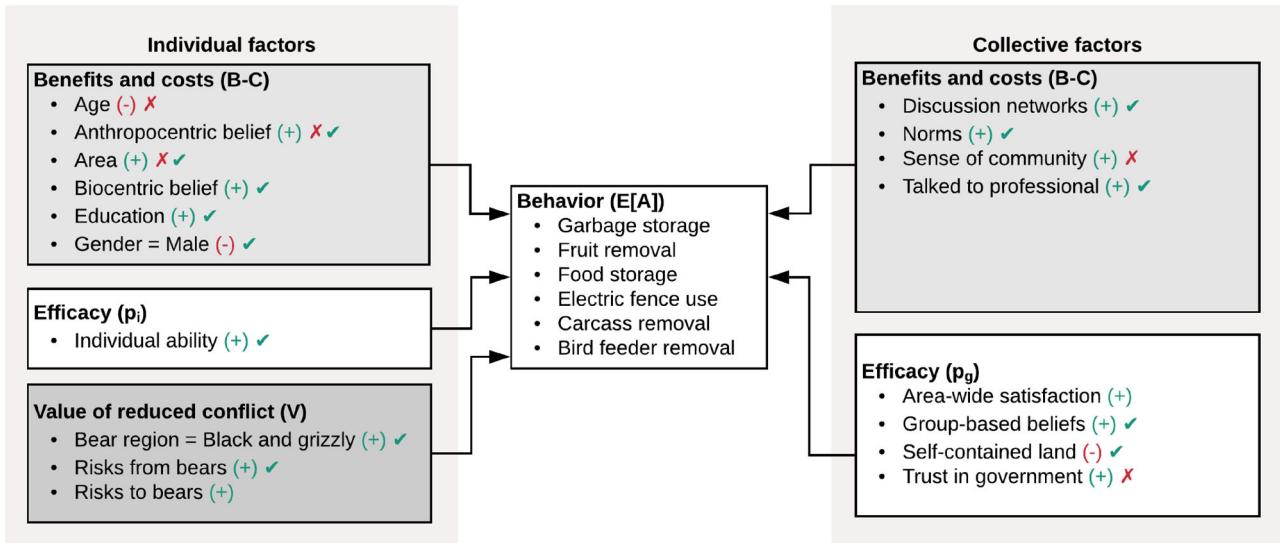
$$E(\mathcal{A}) = [(p_i + p_g) \times V] + B - C.$$

Presumably, individuals who expect high utility from engaging in a behavior will also engage in that behavior; thus, we used whether or not individuals secured attractants as a proxy for their expected utility. We predicted that individuals would secure attractants ( $E[\mathcal{A}]$ ) if they believed there was value in reduced conflict with bears, their individual actions would be effective, their neighbor's actions together would be effective, there were benefits in undertaking the action, and costs were not too high.

**Response variables.**—To determine the expected utility of each action, we asked respondents whether they had taken any of the following 6 actions to secure bear attractants on their property in the past 5 years: use bear-resistant garbage cans, have electric fences around attractants, remove fruit from fruit trees, use bear-resistant pet food or feed storage, remove livestock carcasses, and take down bird feeders during spring and fall. These actions were included in the survey based on collaboration with several natural resource agencies, land trusts, wildlife advocacy groups, the Confederated Salish and Kootenai Tribes, and county land managers in Montana. We tested each response variable independently and assigned a value of 0 if they had not taken the action or 1 if they had (Fig. 3; Tables S1 and S2, available online in Supporting Information).

**Explanatory variables—individual factors.**—We conceptualized explanatory variables based on previous research using the collective interest model (Lubell et al. 2007, Niemiec et al. 2016, Lubeck et al. 2019) and studies on collective action and wildlife coexistence, where each variable was either an individual or collective factor (Fig. 3; Table S1). Individual factors included the value of reduced conflict with bears, personal efficacy, and benefits and costs accrued to the individual that are intrinsic to that individual. To determine how the individual valued reduced conflict with bears, we asked about concerns regarding potential risks from bears on the individual's belongings, family, pets, and abilities (i.e., risks from bears; Lubell et al. 2007, Bruskotter et al. 2009) and concern for the lives of bears (i.e., risks to bears; Lubell et al. 2007). Following Lubell et al. (2007), we predicted that individuals who viewed risks from or to bears as high would be more likely to engage in mitigating behavior. For the bear region variable, we determined whether respondents lived within black or grizzly bear ranges using address location and a spatially explicit geodatabase of extant bear ranges (FWP 2018). Based on previous research that suggests people respond differently to different species (Zinn et al. 1998, Kleiven et al. 2004), we predicted that individuals living in the area with both black and grizzly bears would more highly value reduced conflict with grizzly bears and thus be more likely to undertake mitigative actions than those living with just black bears. To determine personal efficacy, we asked whether or not respondents thought their personal actions could help reduce bear conflict on their property (Lubell et al. 2007, Niemiec et al. 2016, Lubeck et al. 2019) and whether the respondent believed they had enough time, money, and confidence to secure bear attractants (i.e., individual ability). We predicted that individuals with high personal efficacy would be more likely to secure bear attractants.

We conceptualized individual benefits and costs using sociodemographic and psychological measures (Olson 1971, Yung et al. 2015). We predicted that individuals who could afford the cost of securing bear attractants, measured through self-reported variables on income and education level, would be more likely to engage in the behavior (Lubell et al. 2007, Niemiec et al. 2016, Lubeck et al. 2019). We also asked



**Figure 3.** Conceptual model of the individual and collective factors that may influence behavior to secure bear attractants in Montana, USA, 2018. The predicted effect of each variable on uptake of attractant securing behavior is shown with a positive (+) or negative (−) sign next to each variable. Variables with both checks and xs indicate that our results show evidence in support and opposition of our prediction, depending on the behavior model. Variables without a check or x fell out of all final models. We used whether individuals secured attractants as a proxy for their expected utility (E[A]) of engaging in that behavior.

respondents their age and gender, and predicted that older individuals and men would be less likely to secure bear attractants. We also predicted that individuals who owned more land (i.e., area), and thus who were more likely to be ranchers or farmers, would be more likely to secure bear attractants because they would incur higher benefits (*B*) to their livelihoods (Niemiec et al. 2016, Lubeck et al. 2019). We measured the individual psychological benefits of securing bear attractants through biocentric belief and anthropocentric belief scales (Dunlap and Van Liere 1978) and predicted that individuals scoring high on these belief scales would feel benefits of protecting ecological and human-centric values, respectively (Lubell et al. 2007).

**Explanatory variables—collective factors.**—We measured several collective factors including group efficacy and benefits and costs accrued to the individual that are a result of the group (Table S1, Fig. 3). We conceptualized group efficacy through several social capital constructs and problem definitions. Group efficacy variables were the perceived competency of government agencies (i.e., area-wide satisfaction) and trust in government agencies (i.e., trust in government) to manage conflicts with bears (Lubell et al. 2007, Niemiec et al. 2016, Lubeck et al. 2019); beliefs about the group's ability to address the problem (i.e., group-based beliefs), which included measures of reciprocity, influence of collective actions, and belief in the cross-boundary nature of the problem (Lubell et al. 2007, Niemiec et al. 2016, Lubeck et al. 2019); and whether landowners saw their land as self-contained (i.e., self-contained land; Lubeck

et al. 2019). We predicted that individuals with a higher sense of group efficacy would be more likely to engage in mitigative behavior.

We conceptualized collective benefits and costs through social capital and psychological factors (Lubell et al. 2007). We asked respondents about whether or not they perceived injunctive norms (expectations of their peers) and descriptive norms (behaviors of their peers) regarding attractant securing behavior. We predicted that those who perceived norms would be more likely to engage in mitigative behavior so as to increase their social benefits and decrease social sanctions (Lubell et al. 2007, Willcox et al. 2012, Niemiec et al. 2016, Eklund 2019, Sakurai 2019). To determine community engagement and the influence of each land-owner within their social network, we asked respondents whether anyone had asked for or tried to influence their opinion regarding bear attractants (i.e., discussion networks; Lubell et al. 2007, Niemiec et al. 2016, Lubeck et al. 2019). Following Absher et al. (2013), we asked respondents about their sense of community using 4 items in the questionnaire. We predicted that those with high discussion networks and sense of community would have a lower cost of acquiring information on securing bear attractants and more sanctioning from their social circles, and therefore would be more likely to engage in mitigative behavior (Lubell et al. 2007, Janssen 2013, Niemiec et al. 2016, Lubeck et al. 2019). We also included a variable measuring whether or not respondents had talked to a wildlife professional (i.e., talked to professional) and predicted that those who had

would be more likely to engage in mitigation because of the decreased barrier of acquiring information through their social networks (Lubell et al. 2007).

**Scales.**—We used several different scales for explanatory variables. Bear region (black bear or black and grizzly bear) and talked to professional (yes or no) variables were measured on a dichotomous scale. There were 2 survey questions for each of the discussion networks and norms variables, each question on a dichotomous scale. We measured area and age on a continuous scale. We measured gender categorically as male, female, or prefer not to disclose. We measured all other variables on a 5-point Likert scale using unique response anchors (Table S1).

## Analysis

We performed exploratory factor analyses for variable reduction within each of the collective interest model designations ( $p_g$ ,  $p_i$ ,  $V$ ,  $B - C$ ). We used the fa.parallel function in the psych package (Revelle 2019) in R (version 3.6.1; R Core Team 2019), finding minimum residuals through ordinary least squares with an oblique rotation. We measured scale reliability for composite variables using Cronbach's alpha ( $\alpha$ ) with a cut-off of 0.65 (Vaske 2008). For dichotomous questions (about discussion networks and norms), we summed responses to generate composite variables. For all other composite variables, we took the average of responses. Because question non-response was high for the income variable, we removed it from all models. After creating composite variables, we removed all respondents with incomplete data before analysis.

We tested the relationships between explanatory variables and each response variable using independent logistic regression models for each of the 6 attractant securing behaviors. Following methods in Lubeck et al. (2019), Lubell et al. (2007), Niemiec et al. (2016), and Yau (2011), to easily interpret the relationships among variables, we simplified the collective interest model to:

$$E(\text{securing bear attractants}) = p_i + p_g + V + B - C$$

We treated all variables as continuous except for gender, bear region, and talked to professional, which were categorical. We built each logistic regression model with all explanatory variables as the saturated model and did not include any interaction terms. We used backward selection, measuring model fit with the Akaike's Information Criterion (AIC), and sequentially removed terms until the AIC score could not be reduced further (MASS package, stepAIC function; Venables and Ripley 2002). With each final model, we tested the linearity assumption of each continuous variable by examining plots of the logit versus the predicted value for each variable and found no evidence of non-linearity. We looked for influential observations by examining Cook's distance. Although some distances were slightly above the suggested cut-off of  $4/n$ , upon closer examination we found no unusual observations and no standardized residuals above 3, and thus no evidence of influence. We also looked for issues of multicollinearity

among our explanatory variables using variance inflation factors, all of which were below 2 and thus showed no evidence of collinearity (Ott and Longnecker 2015). We used likelihood ratio tests to determine whether each model was significantly different from the saturated and null models. For each model, we tested goodness of fit using the Hosmer-Lemeshow test (ResourceSelection package, hoslem.test function; Lele et al. 2019) across a range of group numbers (4–15) because the test results are sensitive to group number. We also report McFadden's pseudo- $R^2$  (pscl package, pR2 function; Jackman 2017), a proxy for measuring explained variation in logistic regressions. Finally, we used cross-validation to determine how well each model predicted individual behavior by splitting the data into a training set (60%) and a testing set (40%). We used the training set to parameterize the model and determine how often it was able to accurately predict individual behavior in the testing set.

## RESULTS

We received 1,305 at least partially completed surveys from respondents for an overall response rate of 29.5% (Table 1). After removing respondents with no responses to any bear-related questions on the survey, remaining observations totalled 1,272 for an effective response rate for bear questions of 28.7%. Additionally, the bear-related questions on the survey had high non-response in the eastern portion of the state where there are no bears ( $n = 192$  for whom 74% of question responses were left blank or marked as not applicable). Thus, we removed all respondents from the sample who were not georeferenced within either grizzly or black bear ranges, leaving 1,080 respondents from the parts of Montana inhabited by bears (Fig. 1). We fit separate models for each attractant securing behavior and removed respondents who either said the action was not applicable or did not have complete responses to all hypothesized independent variables. Uptake of attractant securing behavior varied depending on the behavior. For example, of the respondents who said the behavior was applicable to them, 13% secured livestock with electric fences, compared to 29% who removed livestock carcasses (Table 1). Respondents were 71–74% male, mean age was 63–65 years old, and the most common education class was a college graduate—a respondent profile consistent with landowner populations in rural states in the western United States (Butler and Butler 2016, USDA 2017). To check for nonresponse bias, we compared respondents and non-respondents across variables in the Montana cadastral dataset (e.g., land value, total value, building value, total property size, and hectares of land in the farm, used for grazing, forested, laying fallow, irrigated, used for wild hay, and unsuitable for farming) with independent  $t$ -tests. We found no significant differences between respondent and non-respondents across these variables ( $P < 0.05$ ; Lindner et al. 2001).

We found that all final models were significant in predicting attractant securing behaviors, with little to no evidence of lack of fit (Table 2). All final models were significantly different ( $P < 0.05$ ) from their null model but

**Table 1.** Scale, collective interest model (CIM) designation, and mean ( $\bar{x}$ ) and standard deviation (SD) of each variable of the saturated models predicting bear attractant securing behavior in Montana, USA, 2018. Means vary across models because each model had a different sample size.

Type	Variable	$\alpha$ (number <sup>a</sup> of items)		CIM <sup>b</sup>		Garbage storage ( $n = 328$ )		Fruit removal ( $n = 265$ )		Food storage ( $n = 275$ )		Electric fence use ( $n = 293$ )		Carcass removal ( $n = 210$ )		Bird feeder removal ( $n = 290$ )		
		Scale	CIM <sup>b</sup>	$\bar{x}^c$	SD	$\bar{x}^c$	SD	$\bar{x}^c$	SD	$\bar{x}^c$	SD	$\bar{x}^c$	SD	$\bar{x}^c$	SD	$\bar{x}^c$	SD	
Response	Action to secure bear attractants	0–1	E(A)	0.23	0.42	0.23	0.42	0.25	0.43	0.13	0.34	0.29	0.46	0.28	0.45			
Explanatory-individual	Age	Continuous	B-C	64.19	12.36	64.08	12.35	63.19	12.47	63.97	12.21	63.9	12.44	64.66	11.98			
	Anthropocentric belief	1–5	B-C	2.32	1.13	2.32	1.11	2.31	1.09	2.38	1.12	2.40	1.17	2.3	1.17	2.3	1.12	
	Area	Continuous	B-C	13.20	951.86	15.00	929.55	16.00	1007.67	14.00	976.93	23.90	1132.22	13.60	971.32			
	Biocentric belief	1–5 <sup>d</sup>	B-C	3.72	1.07	3.66	1.10	3.68	1.07	3.66	1.08	3.63	1.10	3.74	1.06			
	Education	1–5 <sup>d</sup>	B-C	4.00	1.09	4	1.08	4	1.05	4	1.09	4.00	1.05	4	1.05	4	1.08	
	Gender	Female (F), Male (M), No response	B-C	F=26.8%, M=72.3%		F=28.7%, M=70.6%		F=26.2%, M=73.1%		F=26.3%, M=72.7%		F=27.1%, M=71.9%		F=27.1%, M=73.8%				
	Personal efficacy	0.84 (4)	$p_i$	3.46	0.87	3.35	0.85	3.39	0.87	3.38	0.87	3.38	0.87	3.25	0.90	3.46	0.88	
	Bear region		V	B=28.4%, B-G=71.6%		B=32.5%, B-G=67.5%		B=33.1%, B-G=66.9%		B=33.1%, B-G=66.9%		B=31.1%, B-G=68.9%		B=40.0%, B-G=60.0%		B=30.7%, B-G=69.3%		
Explanatory-collective	Risks from bears	0.95 (4)	V	2.13	1.02	2.03	1.01	2.1	1.04	2.11	1.03	2.08	1.07	2.05	0.98			
	Risks to bears		V	3.84	1.22	3.68	1.29	3.74	1.25	3.78	1.24	3.57	1.32	3.79	1.25			
	Discussion	0.79 (2)	0–2	B-C	0.24	0.60	0.18	0.53	0.23	0.61	0.24	0.6	0.19	0.54	0.23	0.59		
	Norms	0.88 (2)	0–2	B-C	0.55	0.81	0.43	0.75	0.43	0.75	0.48	0.78	0.42	0.75	0.52	0.8		
	Sense of community	0.84 (4)	1–5	B-C	3.42	0.75	3.4	0.74	3.38	0.76	3.4	0.76	3.41	0.77	3.41	0.77		
	Talked to professionals		0–1	B-C	0.16	0.37	0.14	0.35	0.17	0.37	0.15	0.36	0.15	0.36	0.16	0.37		
	Area-wide satisfaction		1–5	P <sub>g</sub>	3.21	0.95	3.2	0.91	3.17	0.93	3.21	0.94	3.14	0.99	3.25	0.92		
	Group-based beliefs	0.84 (4)	1–5	P <sub>g</sub>	3.15	0.81	3.03	0.83	3.06	0.83	3.08	0.83	2.97	0.87	3.1	0.84		
	Self-contained land		1–5	P <sub>g</sub>	2.27	0.96	2.33	0.99	2.29	0.97	2.34	0.98	2.41	1.01	2.3	0.94		
	Trust in government		1–5	P <sub>g</sub>	2.38	1.08	2.37	1.08	2.35	1.09	2.35	1.08	2.35	1.12	2.42	1.07		

<sup>a</sup> Cronbach's alpha ( $\alpha$ ) and number of items are shown for composite variables.

<sup>b</sup> E(A) = expected utility of securing attractants, V = value of reduced conflict with bears,  $P_g$  = individual efficacy, B-C = benefits and costs of undertaking the action.

<sup>c</sup> The median is shown for area, mode is shown for education, frequency distributions are shown for gender and bear region variables, and the mean is shown for all other variables.

<sup>d</sup> 1 = grade school, 2 = high school or General Educational Development (GED), 3 = some college, 4 = college graduate, 5 = post graduate.

**Table 2.** Sample size, degrees of freedom, significance and goodness-of-fit tests, and prediction accuracy for each final model predicting bear attractant securing behavior in Montana, USA, 2018.

Test	Garbage storage	Fruit removal	Food storage	Electric fence use	Carcass removal	Bird feeder removal
<i>n</i>	328	265	275	293	210	290
Degrees of freedom	8	11	11	8	11	8
LR test (null) <sup>a</sup>	<0.001	<0.001	<0.001	<0.001	<0.001	<0.001
LR test (saturated) <sup>a</sup>	0.96	0.58	0.81	0.81	0.68	0.81
HLGOF (tests < 0.05) <sup>b</sup>	0	1	0	0	2	0
Prediction accuracy with cross-validation	73%	76%	66%	75%	64%	65%

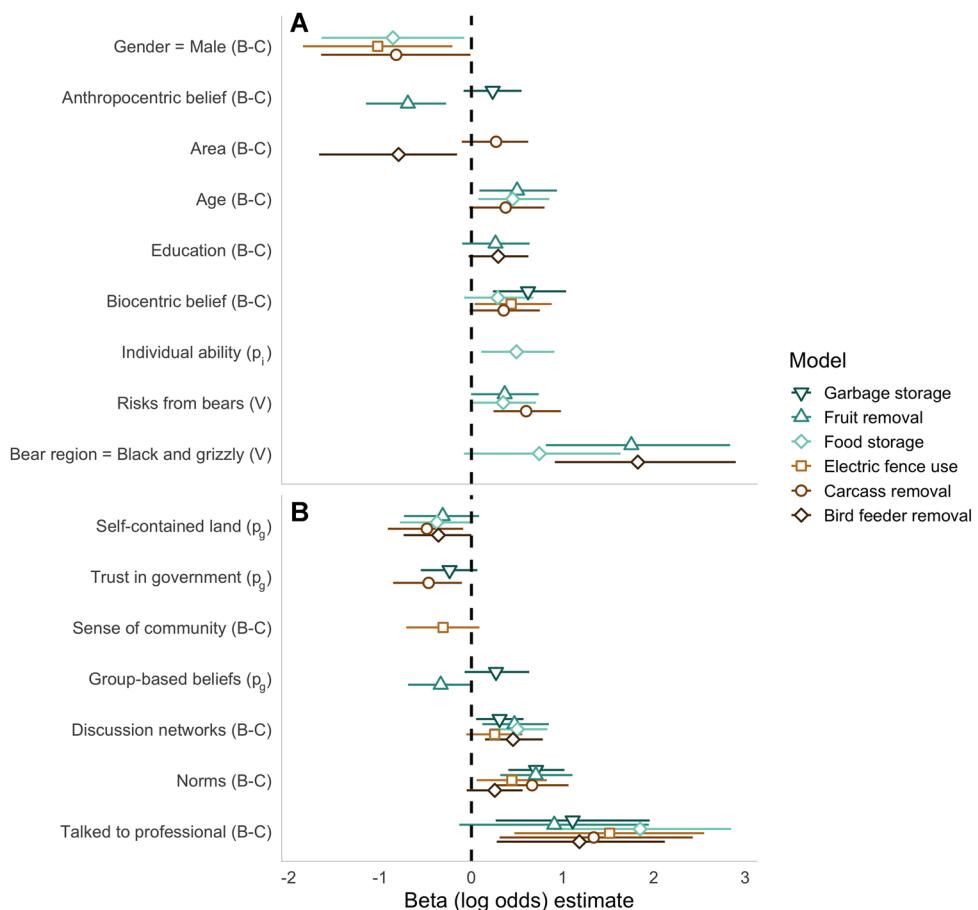
<sup>a</sup> Likelihood ratio (LR) tests against the null indicate model significance (when  $P < 0.05$ ), whereas LR tests against the saturated model indicate that there is no significant difference between the reduced model and the saturated model (when  $P > 0.05$ ).

<sup>b</sup> We used the Hosmer-Lemeshow goodness-of-fit (HLGOF) test with 4–15 groups per model to test lack of fit—the number reported here is the number of times out of 12 that the test was significant (i.e., evidence of lack of fit).

not significantly different from their saturated model, suggesting that variables were significant predictors of attractant securing behavior and that the reduced, less complex models, performed just as well as their saturated counterparts. Of the 12 Hosmer-Lemeshow tests conducted for each model, only 1 test was significant for the fruit removal model and 2 for the carcass removal model, providing little evidence of poor model fit for all models. McFadden's

pseudo- $R^2$  ranged from 0.27 to 0.33 and prediction accuracy using cross-validation ranged from 64–76% across models.

Significant predictors varied by attractant securing behavior (Fig. 4; Tables 3 and 4), yet all models retained both individual and collective explanatory variables. The most consistent collective variable predicting attractant securing behavior was talked to professional, which had among the largest effect sizes across variables in all models (odds



**Figure 4.** Log odds estimates for parameters in each final model after model selection (based on Akaike's Information Criterion) for A) individual and B) collective factors that may influence behavior to secure bear attractants in Montana, USA, 2018. The triangle, diamond, square, or circle symbols denote the point estimate and the bars denote the 95% confidence interval. Collective interest model designations are V = value of the public good produced by the action,  $p_i$  = personal efficacy,  $p_g$  = group efficacy, B-C = benefits and costs.

**Table 3.** Akaike's Information Criterion (AIC) and McFadden's pseudo  $R^2$  for final models and for final models predicting bear attractant securing behavior in Montana, USA, 2018, and with collective variables removed.

Model	Factors in model	Parameters	AIC	$\Delta\text{AIC}^a$	McFadden's $R^2$
Garbage storage	Individual + collective	Talked to professional + effectiveness of group + discussion networks + norms + trust in government + biocentric belief + anthropocentric belief	274.89	69.44	0.27
	Individual	Biocentric belief + anthropocentric belief	344.33	0.04	0.04
Fruit removal	Individual + collective	Talked to professional + bear region + effectiveness of group + discussion networks + norms + self-contained land + risks from bears + age + anthropocentric belief + education	214.66	37.29	0.33
	Individual	Age + anthropocentric belief + education + risks from bears + bear region	251.95	0.17	0.17
Food storage	Individual + collective	Talked to professional + gender + bear region + discussion networks + self-contained land + risks from bears + personal efficacy + age + biocentric belief	226.27	47.20	0.34
	Individual	Age + biocentric belief + gender + personal efficacy + risks from bears + bear region	273.47	0.16	0.16
Electric fence use	Individual + collective	Talked to professional + gender + discussion networks + norms + sense of community + biocentric belief	188.39	31.60	0.25
	Individual	Biocentric belief + gender	219.99	0.08	0.08
Carcass removal	Individual + collective	Talked to professional + gender + area + norms + self-contained land + risks from bears + trust in government + age + biocentric belief	196.77	32.03	0.31
	Individual	Area + age + biocentric belief + gender + risks from bears	228.80	0.15	0.15
Bird feeder removal	Individual + collective	Talked to professional + bear region + area + discussion networks + norms + self-contained land + education	261.18	41.02	0.29
	Individual	Area + education + bear region	302.20	0.15	0.15

<sup>a</sup>  $\Delta\text{AIC}$  is the difference in AIC scores between the model with only individual variables and the model with individual and collective variables.

ratio = 2.48–6.35) and was significant in all ( $P < 0.001$  to 0.01) except the fruit removal model ( $P = 0.08$ ). Other important collective variables across most models included norms (odds ratio = 1.29–2.03,  $P < 0.001$  to 0.1), discussion networks (odds ratio = 1.29–1.65,  $P < 0.01$  to 0.1), and self-contained land (odds ratio = 0.61–0.73,  $P = 0.02$  to 0.1).

Several individual variables explained significant variance in attractant securing behavior. The most consistent individual variable predicting attractant securing behavior was biocentric belief (odds ratio = 1.34–1.86,  $P < 0.01$  to 0.1), which persisted in most final models, except the fruit and bird feeder removal models. The bear region variable had the largest effect size for the black and grizzly region across all individual variables but was only present in the fruit removal (odds ratio = 5.77,  $P < 0.001$ ), food storage (odds ratio = 2.1,  $P = 0.09$ ), and bird feeder removal (odds ratio = 6.19,  $P < 0.001$ ) models. Gender (coded as males = 1, females = 0) also had a large effect size in the food storage (odds ratio = 0.42,  $P = 0.03$ ), electric fence use (odds ratio = 0.36,  $P = 0.01$ ), and carcass removal (odds ratio = 0.44,  $P < 0.05$ ) models. Risks from bears had a moderate effect size in the fruit removal (odds ratio = 1.44,  $P = 0.05$ ), food storage (odds ratio = 1.42,  $P = 0.05$ ) and carcass removal (odds ratio = 1.82,  $P = 0.001$ ) models. Risks to bears and area-wide satisfaction with bear management dropped from all final models.

Consistent with our hypothesis and predictions, collective variables had large effect sizes, high significance, and were important for explaining variation in all models. For example, people who had spoken to a wildlife professional were as much as 6.35 times as likely to secure bear attractants than those who had not, holding all other variables constant. Furthermore, the odds of securing bear attractants increased by as much as 2 times for every unit increase in perceived norms (in the garbage storage, fruit removal, and carcass removal models) and by as much as 1.65 times for every unit increase in discussion networks (in the food storage model), holding all else constant. Conversely, the odds of securing bear attractants were reduced by as much as 39% for every unit increase in self-contained land beliefs (in the carcass removal model), holding all else constant. When we removed collective variables from models initially built with both collective and individual variables, AIC scores increased across all models, indicating reduced model fit. Furthermore, removing collective factors from models decreased McFadden's pseudo- $R^2$  by 49% to as much as 85% (Table 3).

## DISCUSSION

Understanding how humans and large carnivores might coexist is an increasingly common goal among those seeking to recover large carnivore populations while maintaining human well-being (Nyhus 2016). Securing attractants reduces the likelihood of interacting with wildlife, thereby reducing potential conflict and increasing the possibility of coexistence (Sillero-Zubiri et al. 2007). Our results demonstrate that collective factors affect 6 different individual attractant securing behaviors that

**Table 4.** Odds ratios (OR), 95% confidence intervals (CI) and *P*-values based on Wald tests for parameters in each final model after model selection. Final models predict bear attractant securing behavior in Montana, USA, 2018 and were selected based on the Akaike's Information Criterion, not Wald tests.

Type	Variable	Garbage storage		Fruit removal		Food storage		Electric fence use		Carcass removal		Bird feeder removal		
		CIM <sup>a</sup>	OR (95% CI)	Wald <i>P</i>	OR (95% CI)	Wald <i>P</i>	OR (95% CI)	Wald <i>P</i>	OR (95% CI)	Wald <i>P</i>	OR (95% CI)	Wald <i>P</i>	OR (95% CI)	Wald <i>P</i>
Individual	Age	0.15 (0.1, 0.22)	<0.001 (0.02, 0.12)	0.05 (1.65, 1.09)	<0.001 (0.07, 0.43)	0.18 (1.57, 1.08)	<0.001 (0.08, 0.3)	0.16 (0.02, 2.35)	<0.001 (0.24, 0.95)	0.48 (1.45, 0.98)	0.04 (0.02, 2.23)	0.05 (0.19, 0.85)	<0.001 (0.02, 0.12)	<0.001
Anthropocentric belief		1.26 (0.92, 1.73)	0.1 (0.50, 0.32)	0.002 (0.32, 0.76)										0.07
Area		B-C												
Biocentric belief		B-C	1.86 (1.27, 2.82)	0.002 (0.90, 1.89)	0.1 (1.30, 0.2)									
Education		B-C												
Gender = male		B-C												
Individual ability		P <sub>i</sub>												
Bear region = black and grizzly		V												
Risks from bears		V												
Collective	Discussion networks	B-C	1.36 (1.05, 1.77)	0.02 <0.001	1.60 (1.13, 2.33)	0.01 <0.001	1.65 (1.22, 2.3)	0.002 <0.001	1.29 (0.95, 1.75)	0.1 (1.06, 2.28)	1.82 (1.27, 2.67)	0.001 (1.32, 2.90)	6.19 (2.49, 18.09)	<0.001
Norms		B-C	2.03 (1.50, 2.77)		2.02 (1.37, 3.03)		1.56 (1.06, 2.28)		0.02 (0.49, 1.09)	1.94 (0.73, 0.73)	<0.001 (1.36, 11.30)	1.58 (0.95, 1.75)	0.004	
Sense of community		B-C												
Talked to professional		B-C	3.03 (1.31, 7.05)	0.01 (0.93, 1.88)	2.48 (0.88, 6.98)	0.08 (0.50, 1.02)	6.35 (2.46, 17.2)	0.0002 (1.60, 12.80)	4.55 (0.49, 1.09)	0.004 (1.36, 11.30)	3.82 (1.60, 12.80)	0.01 (0.4, 0.91)	3.27 (0.42, 0.90)	0.01
Group-based beliefs		P <sub>g</sub>												
Self-contained land		P <sub>g</sub>												
Trust in government		P <sub>g</sub>	0.79 (0.57, 1.07)	0.1										

<sup>a</sup> Collective interest model (CIM) designation: *V* = value of reduced conflict with bears, P<sub>i</sub> = individual efficacy, B-C = benefits and costs of undertaking the action.

could minimize negative interactions with bears. Indeed, collective factors were more important than individual factors in influencing over half of the different behaviors. For example, talking to a professional had the largest effect size in the garbage storage, food storage, electric fence use, and carcass removal models, and had the second highest effect size in the fruit and bird feeder removal models. Furthermore, social norms had the second highest effect size in the garbage storage and carcass removal models, and the variable discussion networks was the second most ubiquitous predictor across behaviors. These results suggest that although often overlooked, collective factors play a critical role in influencing individual behavior (Niemiec et al. 2016).

Our findings are particularly relevant for wildlife managers aiming to influence individual actions on private lands, where collective benefits amount to reduced conflict with wildlife across the landscape. Although there is increasing research on collective activities like participatory or deliberative decision-making and stakeholder engagement in wildlife management (Riley et al. 2003, Ban et al. 2013, Clark and Rutherford 2014, Lundmark and Matti 2015, Biggs et al. 2017), very little research examines how individual perceptions of collective factors—such as norms (Martin and McCurdy 2009, Willcox et al. 2012, Sakurai et al. 2015, Young 2018, Eklund 2019), discussion networks, and group-based beliefs— influence individual behaviors. If the current philosophy of increasing or stabilizing wildlife populations through improved coexistence between people and wildlife is to be successful, effective prevention and mitigation is needed. Some of these strategies will require individuals, landowners included, to voluntarily make contributions to the collective good. Collective factors may be an important missing piece of the puzzle for voluntary actions toward preventing and mitigating conflict with wildlife on private lands. Where voluntary adoption of bear-friendly behavior is insufficient, structural fixes may be needed (Heberlein 2012); for example, municipalities may unilaterally switch to bear-resistant garbage cans, as in Red Lodge, Montana (FWP 2008).

Collective factors are highly influential and more likely to change in response to outreach efforts, whereas individual factors tend to be more fixed. For example, it is possible to change normative beliefs with outreach efforts (Heberlein 2012, Veríssimo et al. 2019), whereas age, education, gender, and geographic location are relatively stable. Value orientations, too, are unlikely to change over time or in response to interventions (Manfredo et al. 2017). By focusing on collective factors, practitioners orient their efforts toward more malleable factors where they may find greater success inspiring attractant securing behavior. Although the efficacy of outreach campaigns to reduce wildlife conflict is rarely tested (Gore et al. 2016), with only a few examples in the literature (Saypanya et al. 2013; Lu et al. 2016, 2018), our findings echo  $\geq 1$  study that reported norms can be powerful tools in wildlife-related behavior change campaigns. In a study on the use of bear-resistant storage containers in Colorado, USA, Young (2018) reported that although there were no differences in uptake of

attractant securing behavior between people who received messages that emphasized the benefits of securing attractants versus those receiving messages about the risks of not securing attractants, subjective norms did significantly predict intention to secure bear attractants. Outreach that simply conveys the risks posed by bears misses an opportunity to highlight collective factors and is likely to be less effective than those that incorporate a normative appeal (Heberlein 2012, Dietsch et al. 2018).

Mirroring past research, our findings indicate that mitigating conflict with wildlife varies by species and by specific behavior. For example, holding all else constant, respondents were more likely to remove bird feeders and fruit from fruit trees, and store food appropriately when they lived in an area with both black and grizzly bears, rather than just with black bears. This finding is consistent with other wildlife coexistence research that suggests people's cognitions and behaviors vary depending on the species with which conflict is possible (Zinn et al. 1998, Kleiven et al. 2004). Regarding behavior specificity, of the behaviors applicable to respondents, electric fence use had the lowest uptake and carcass removal had the highest. Garbage storage was the most applicable behavior to respondents but had relatively moderate levels of uptake. Although there was consistency among models, there were also some substantial differences in the factors that influenced each behavior. In addition to each behavior-specific model, we attempted to create a composite behavior model using several different alternatives (see Composite Response Variable Attempts in Supporting Information); however, cross-validation of these models resulted in low prediction accuracies (51–63%) compared to the prediction accuracies of the behavior-specific models (64–76%; Table 2). These results are consistent with foundational theory and past research findings that suggest that specificity is particularly important when trying to predict behavior change or adoption (Ajzen and Fishbein 1980, Lubeck et al. 2019).

Although our hypothesis that collective factors would explain significant additional variation above individual factors was supported by the evidence, a few results contradicted specific predictions but still demonstrate the utility of a collective action approach to wildlife-related behavior change. For example, we predicted that trust in government would increase group efficacy and therefore increase the likelihood that an individual would partake in a collective behavior (Lubell et al. 2007, Niemiec et al. 2016). Instead, we found the opposite—respondents in our sample who trusted the government were less likely to use bear-resistant garbage storage and remove livestock carcasses. This finding suggests a free-rider effect may be emergent, whereby individuals' contributions to collective efforts are suppressed when the public good can be achieved (or achieved enough) without their participation (Sandler 2015). This result is consistent with other research that shows a complicated relationship between trust and public engagement (Smith et al. 2013, Stern and Coleman 2015, Parkins et al. 2017). Similarly, negative effects for sense of community and group-based beliefs in some models further support evidence of free-riding.

A few of our predictions were contradicted by the data. For example, respondents with high anthropocentric beliefs were less likely to remove fruit from their fruit trees, perhaps because they had low instrumental use for bears or placed a high value on fruit and thus accrued less net benefit from mitigating conflict. Additionally, respondents with large plots of land were less likely to remove bird feeders in spring and fall months. This result may be because individuals who own large tracts of land are likely ranchers or farmers who have other, more valuable bear attractants (e.g., livestock) to secure than bird feeders.

Future research should seek to address limitations we encountered in this study. Although not uncharacteristically low, our response rate could have been higher, especially for bear-related questions posed to respondents living outside of black and grizzly bear ranges. Salience may be low in areas into which bears have not yet expanded, suggesting that future survey research may require incentives or other methods of engagement. Second, the talked to professional variable in our models may be tautological, such that individuals who seek information from wildlife professionals may be doing so because they are already interested in securing bear attractants, rather than developing an interest in those behaviors because of interactions with a wildlife professional. Regardless, we believe this variable indicates the importance of reducing the costs of acquiring information, communicating social expectation, and bolstering efficacy beliefs, thus, highlighting the importance of this investment for wildlife agencies. When we reran our analyses without this variable, our final models stayed relatively stable, suggesting that even if we discount the effect of talking to a wildlife professional, other collective variables remain important for predicting attractant securing behavior (see Analysis Without the Talked to Professional Variable in Supporting Information). Third, some variables were proxies for the concept we were trying to measure. For example, it will likely be helpful for future research to measure respondents' direct experiences with bears (rather than using bear region as a proxy), which influences human reactions and behavior (Hudenko 2012). Additionally, quantifying direct benefits and costs of human-bear interactions on people's livelihoods (e.g., ranching, tourism) may be constructive.

Many questions remain regarding the collective nature of securing bear attractants and human-wildlife interaction more broadly. Future research could examine if or how group and individual efficacy modify the valuation of attractant securing behaviors (Finkel et al. 1989), rather than assuming an additive approach as in our models. Another future step would be to examine whether there are interaction effects between group and individual efficacy. For example, does the perceived efficacy of the group vary by how individuals perceive their own efficacy? Although use of normative appeals is well-appreciated in commercial marketing, few examples exist of changing human behavior to reduce conflict with wildlife (Veríssimo et al. 2019). Future research could also test interventions to determine whether a change in collective factors (assuming interventions can change collective factors) results in uptake of actions that

aim to mitigate human conflicts with bears and other carnivore species.

## MANAGEMENT IMPLICATIONS

Managers and outreach coordinators could benefit from leveraging collective factors when addressing human-bear conflict. Managers can use social norms to promote bear-friendly behavior by increasing both descriptive (e.g., people like you are securing bear attractants) and injunctive (e.g., people you respect believe you should secure your bear attractants) messaging in their campaigns. Wildlife agencies encouraging landowners to secure bear attractants would be wise to invest in bear specialists who can interact with the public face to face and build relationships with influential members of relevant social networks.

In light of the recent successful efforts to increase and stabilize some large carnivore populations in the United States, there is a need to mitigate conflict between people and wildlife. Given the collective interest at stake and collective action required for success, adopting a collective action frame to understand this issue may facilitate new and effective strategies for managers promoting human-wildlife coexistence.

## ACKNOWLEDGMENTS

We acknowledge that our study area is on the ancestral lands of Indigenous peoples, including the A'aninin (Gros Ventre), Amskapi/Piikani (Blackfeet), Annishinabe (Chippewa/Ojibway), Annishinabe/Métis (Little Shell Chippewa), Apsáalooke (Crow), Ktunaxa/Ksanka (Kootenai), Lakota, Dakota (Sioux), Nakoda (Assiniboine), Ne-i-yah-wahk (Plains Cree), Qíispé (Pend d'Oreille), Seliš (Salish), and Tsétséhéstáhese/So'taahe (Northern Cheyenne). We honor the path they have always shown us in caring for this place for the generations to come. We thank the landowners who responded to our survey and E. C. Palm for making figure 1. We also thank the anonymous reviewers for their insights and contributions. We gratefully acknowledge funding support from the Missoula County Weed District, Montana Department of Natural Resources and Conservation, Defenders of Wildlife, Noxious Weed Education Campaign, Gallatin Valley Land Trust, Montana Department of Agriculture, Montana FWP, Montana State Extension, the W.A. Franke College of Forestry and Conservation, and the National Science Foundation's Established Program to Stimulate Competitive Research.

## LITERATURE CITED

Absher, J. D., J. J. Vaske, and K. M. Lyon. 2013. Overcoming barriers to firewise actions by residents. Joint Fire Science Program, St. Albany, California, USA.

Ajzen, I., and M. Fishbein. 1980. Understanding attitudes and predicting social behavior. Prentice-Hall, Englewood Cliffs, New Jersey, USA.

Asheim, L. J., and I. Mysterud. 2005. External effects of mitigating measures to reduce large carnivore predation on sheep. *Journal of Farm Management* 12:206–213.

Ban, N. C., M. Mills, J. Tam, C. C. Hicks, S. Klain, N. Stoeckl, M. C. Bottrill, J. Levine, R. L. Pressey, T. Satterfield, et al. 2013. A social-ecological approach to conservation planning: embedding social considerations. *Frontiers in Ecology and the Environment* 11:194–202.

Baruch-Mordo, S., S. W. Breck, K. R. Wilson, and D. M. Theobald. 2008. Spatiotemporal distribution of black bear–human conflicts in Colorado, USA. *Journal of Wildlife Management* 72:1853–1862.

Beier, P. 1991. Cougar attacks on humans in the United States and Canada. *Wildlife Society Bulletin* 19:403–412.

Bhatia, S., S. M. Redpath, K. Suryawanshi, and C. Mishra. 2020. Beyond conflict: exploring the spectrum of human–wildlife interactions and their underlying mechanisms. *Oryx* 54:621–628.

Biggs, D., R. Cooney, D. Roe, H. T. Dublin, J. R. Allan, D. W. S. Challender, and D. Skinner. 2017. Developing a theory of change for a community-based response to illegal wildlife trade. *Conservation Biology* 31:5–12.

Bjornlie, D. D., F. T. Van Manen, M. R. Ebinger, M. A. Haroldson, D. J. Thompson, and C. M. Costello. 2014. Whitebark pine, population density, and home-range size of grizzly bears in the Greater Yellowstone Ecosystem. *PLoS ONE* 9(2):e88160.

Bradley, E. H., and D. H. Pletscher. 2005. Assessing factors related to wolf depredation of cattle in fenced pastures in Montana and Idaho. *Wildlife Society Bulletin* 33:1256–1265.

Bruskotter, J. T., J. J. Vaske, and R. H. Schmidt. 2009. Social and cognitive correlates of Utah residents' acceptance of the lethal control of wolves. *Human Dimensions of Wildlife* 14:119–132.

Butler, B. J., and S. M. Butler. 2016. Family forest ownerships with 10+ acres in Montana, 2011–2013. United States Department of Agriculture, Newtown Square, Pennsylvania, USA.

Campbell, J. M., and K. J. Mackay. 2003. Attitudinal and normative influences on support for hunting as a wildlife management strategy. *Human Dimensions of Wildlife* 8:181–198.

Carter, N. H., A. Baeza, and N. R. Magliocca. 2020. Emergent conservation outcomes of shared risk perception in human–wildlife systems. *Conservation Biology* 34:903–914.

Ceașu, S., R. A. Graves, A. K. Killion, J. C. Svennning, and N. H. Carter. 2019. Governing trade-offs in ecosystem services and disservices to achieve human–wildlife coexistence. *Conservation Biology* 33:543–553.

Chong, D. 1991. Collective action and the civil rights movement. University of Chicago Press, Chicago, Illinois, USA.

Clark, S. G. and M. B. Rutherford, editors. 2014. Large carnivore conservation: integrating science and policy in the North American West. University of Chicago Press, Chicago, Illinois, USA.

Colorado Parks and Wildlife. 2015. Human–bear conflicts. Colorado Parks and Wildlife, Denver, USA.

Current Results. 2021. Montana weather averages. <<https://www.currentresults.com/Weather/Montana/average-montana-weather.php>>. Accessed 6 Apr 2021.

Dietsch, A. M., K. M. Slagle, S. Baruch-Mordo, S. W. Breck, and L. M. Ciarniello. 2018. Education is not a panacea for reducing human–black bear conflicts. *Ecological Modelling* 367:10–12.

Dillman, D. A., J. D. Smyth, and L. M. Christian. 2014. Internet: the tailored design method. Wiley, Hoboken, New Jersey, USA.

Dunlap, R. E., and K. D. Van Liere. 1978. The "new environmental paradigm". *Journal of Environmental Education* 9:10–19.

Eklund, A. 2019. On the other side of the fence: multidisciplinary perspectives on intervention use to prevent large carnivore attacks on domestic animals in Sweden. Dissertation, Swedish University of Agricultural Sciences, Uppsala, Sweden.

Finkel, S. E., and E. N. Muller. 1998. Rational choice and the dynamics of collective political action: evaluating alternative models with panel data. *American Political Science Review* 92:37–49.

Finkel, S. E., E. N. Muller, and K.-D. Opp. 1989. Personal influence, collective rationality, and mass political action. *American Political Science Review* 83:885–903.

Frank, B., J. A. Glikman, and S. Marchini, editors. 2019. Human–wildlife interactions: turning conflict into coexistence. Cambridge University Press, Cambridge, United Kingdom.

Frankson, R., K. Kunkel, S. Champion, and D. Easterling. 2017. Montana state climate summary. NOAA. <<https://statesummaries.ncics.org/chapter/mt/>>. Accessed 21 Jan 2021.

Garschelis, D. L., B. K. Scheick, D. L. Doan-Crider, J. J. Beechman, and M. E. Obbard. 2016. *Ursus americanus*. The IUCN Red List of Threatened Species 2016:e.T41687A114251609.

Gore, M. L., B. A. Knuth, P. D. Curtis, J. E. Shanahan, M. L. Gore, B. A. Knuth, P. D. Curtis, and J. E. Shanahan. 2016. Education programs for reducing American black bear–human conflict: Indicators of success? *Ursus* 17:75–80.

Graham, S., A. L. Metcalf, N. Gill, R. Niemic, C. Moreno, T. Bach, V. Ikuategbe, L. Hallstrom, Z. Ma, and A. Lubeck. 2019. Opportunities for better use of collective action theory in research and governance for invasive species management. *Conservation Biology* 33:275–287.

Halfpenny, J. C., M. R. Sanders, and K. A. McGrath. 1991. Human–lion interactions in Boulder County, Colorado: past, present, and future. Pages 10–16 in C. E. Braun, editor. *Mountain lion–human interaction*. Colorado Division of Wildlife, Denver, USA.

Heberlein, T. A. 2012. Navigating environmental attitudes. Oxford University Press, New York, New York, USA.

Honda, T., Y. Miyagawa, H. Ueda, and M. Inoue. 2009a. Effectiveness of newly-designed electric fences in reducing crop damage by medium and large mammals. *Mammal Study* 34:13–17.

Honda, T., Y. Yoshida, and T. Nagaike. 2009b. Predictive risk model and map of human–Asiatic black bear contact in Yamanashi Prefecture. Central Japan. *Mammal Study* 34:77–84.

Hudenko, H. W. 2012. Exploring the influence of emotion on human decision making in human–wildlife conflict. *Human Dimensions of Wildlife* 17:16–28.

Interagency Grizzly Bear Committee. 2020. Current status of threatened grizzly bear populations and their recovery. <<http://igbconline.org/conserving-grizzly-populations-2/>>. Accessed 13 Jan 2020.

Jackman, S. 2017. pscl: classes and methods for R developed in the Political Science Computational Laboratory. United States Studies Centre, University of Sydney. <<https://github.com/atahk/pscl/>>. Accessed 4 Apr 2020.

Janssen, M. A. 2013. The role of the state in governing the commons: experimental results. *Ecology and Society* 18:4.

Kendall, K. C., T. A. Graves, J. A. Royle, A. C. Macleod, K. S. McKelvey, J. Boulanger, and J. S. Waller. 2019. Using bear rub data and spatial capture–recapture models to estimate trend in a brown bear population. *Scientific Reports* 9:1–11.

Kendall, K. C., A. C. Macleod, K. L. Boyd, J. Boulanger, J. A. Royle, W. F. Kasworm, D. Paetkau, M. F. Proctor, K. Annis, and T. A. Graves. 2016. Density, distribution, and genetic structure of grizzly bears in the Cabinet–Yaak Ecosystem. *Journal of Wildlife Management* 80:314–331.

Kleiven, J., T. Bjerke, and B. P. Kaltenborn. 2004. Factors influencing the social acceptability of large carnivore behaviours. *Biodiversity and Conservation* 13:1647–1658.

Knox, J., K. Ruppert, B. Frank, C. C. Sponarski, and J. A. Glikman. 2021. Usage, definition, and measurement of coexistence, tolerance and acceptance in wildlife conservation research in Africa. *Ambio* 50:301–313.

Krafcik Holland, K., L. R. Larson, and R. B. Powell. 2018. Characterizing conflict between humans and big cats *Panthera* spp: a systematic review of research trends and management opportunities. *PLoS ONE* 13(9):e0203877.

Lele, S. R., J. L. Keim, and P. Solymos. 2019. ResourceSelection: resource selection (probability) functions for use-availability data. R package version 0.3-5. <<https://cran.r-project.org/package=ResourceSelection>>. Accessed 4 Apr 2020.

Lindner, J. R., T. H. Murphy, and G. E. Briers. 2001. Handling non-response in social science research. *Journal of Agricultural Education* 42:43–53.

Lischka, S. A., T. L. Teel, H. E. Johnson, S. E. Reed, S. Breck, A. Don Carlos, and K. R. Crooks. 2018. A conceptual model for the integration of social and ecological information to understand human–wildlife interactions. *Biological Conservation* 225:80–87.

Lu, H., W. F. Siemer, M. S. Baumer, and D. J. Decker. 2018. Exploring the role of gain versus loss framing and point of reference in messages to reduce human–bear conflicts. *Social Science Journal* 55:182–192.

Lu, H., W. F. Siemer, M. S. Baumer, D. J. Decker, and A. Gulde. 2016. Effects of message framing and past experience on intentions to prevent human–coyote conflicts. *Human Dimensions of Wildlife* 21:506–521.

Lubeck, A. A., A. L. Metcalf, C. L. Beckman, L. Yung, and J. W. Angle. 2019. Collective factors drive individual invasive species control behaviors: evidence from private lands in Montana, USA. *Ecology and Society* 24:32.

Lubell, M., S. Zahran, and A. Vedlitz. 2007. Collective action and citizen responses to global warming. *Political Behavior* 29:391–413.

Lundmark, C., and S. Matti. 2015. Exploring the prospects for deliberative practices as a conflict-reducing and legitimacy-enhancing tool: the case of Swedish carnivore management. *Wildlife Biology* 21:147–156.

Mace, R. D., and T. Chilton-Radandt. 2011. Black bear harvest research & management in Montana. Montana Department of Fish, Wildlife & Parks, Wildlife Division, Helena, USA.

Manfredo, M. J., J. T. Bruskotter, T. L. Teel, D. Fulton, S. H. Schwartz, R. Arlinghaus, S. Oishi, A. K. Uskul, K. Redford, S. Kitayama, et al. 2017. Why social values cannot be changed for the sake of conservation. *Conservation Biology* 31:772–780.

Marchini, S., and D. W. Macdonald. 2012. Predicting ranchers' intention to kill jaguars: case studies in Amazonia and Pantanal. *Biological Conservation* 147:213–221.

Marley, J., A. Hyde, J. H. Salkeld, M. C. Prima, L. Parrott, S. E. Senger, and R. C. Tyson. 2017. Does human education reduce conflicts between humans and bears? An agent-based modelling approach. *Ecological Modelling* 343:15–24.

Marley, J., J. H. Salkeld, T. Hamilton, S. E. Senger, R. C. Tyson, and L. Parrott. 2019. Individual-based modelling of black bear (*Ursus americanus*) foraging in Whistler, BC: reducing human-bear interactions. *Ecological Modelling* 407:108725.

Martin, S. R., and K. McCurdy. 2009. Wilderness food storage in Yosemite: using the theory of planned behavior to understand backpacker canister use. *Human Dimensions of Wildlife* 14:206–218.

Montana Department of Fish, Wildlife, & Parks [FWP]. 2008. Bear-resistant trash cans successful in Red Lodge. <[http://fwp.mt.gov/news/newsReleases/headlines/nr\\_2890.html](http://fwp.mt.gov/news/newsReleases/headlines/nr_2890.html)>. Accessed 16 Oct 2020.

Montana Department of Fish, Wildlife, & Parks [FWP]. 2018. Generalized distribution of black and grizzly bears in Montana. <[http://gis-mtfwp.opendata.arcgis.com/datasets/b59040cc67f742f1a0f1e72c05b2892b\\_0](http://gis-mtfwp.opendata.arcgis.com/datasets/b59040cc67f742f1a0f1e72c05b2892b_0)>. Accessed 3 Apr 2020.

Montana Department of Fish, Wildlife, & Parks [FWP]. 2020. Black bear. <<http://fwp.mt.gov/fishAndWildlife/management/blackBear/>>. Accessed 15 Oct 2020.

Montana State Library. 2019. Montana cadastral mapping project. <<http://svc.mt.gov/msl/mtcadastral>>. Accessed 10 Feb 2020.

Morehouse, A. T., and M. S. Boyce. 2017. Troublemaking carnivores: conflicts with humans in a diverse assemblage of large carnivores. *Ecology and Society* 22:4.

Mott, N., and J. Burnham. 2019. Timeline: a history of grizzly bear recovery in the lower 48 states. Montana Public Radio. <<https://www.mtpr.org/post/timeline-history-grizzly-bear-recovery-lower-48-states>>. Accessed 13 Jan 2020.

Niemiec, R. M., N. M. Ardoine, C. B. Wharton, and G. P. Asner. 2016. Motivating residents to combat invasive species on private lands: social norms and community reciprocity. *Ecology and Society* 21:30.

Niemiec, R. M., S. McCaffrey, and M. S. Jones. 2020. Clarifying the degree and type of public good collective action problem posed by natural resource management challenges. *Ecology and Society* 25:30.

Nyhus, P. J. 2016. Human-wildlife conflict and coexistence. *Annual Review of Environment and Resources* 41:143–171.

Olson, M. 1971. The logic of collective action: public goods and the theory of groups. Harvard University Press, Cambridge, Massachusetts, USA.

Osipova, L., M. M. Okello, S. J. Njumbi, S. Ngene, D. Western, M. W. Hayward, and N. Balkenhol. 2018. Fencing solves human-wildlife conflict locally but shifts problems elsewhere: a case study using functional connectivity modelling of the African elephant. *Journal of Applied Ecology* 55:2673–2684.

Ostrom, E. 1990. Governing the commons: the evolution of institutions for collective action. Cambridge University Press, Cambridge, United Kingdom.

Ostrom, E. 1998. A behavioral approach to the rational choice theory of collective action: Presidential Address, American Political Science Association, 1997. *American Political Science Review* 92:1–22.

Ott, R. L., and M. T. Longnecker. 2015. An introduction to statistical methods and data analysis. Seventh edition. Cengage Learning, Boston, Massachusetts, USA.

Parkins, J. R., T. Beckley, L. Comeau, R. C. Stedman, C. L. Rollins, and A. Kessler. 2017. Can distrust enhance public engagement? Insights from a national survey on energy issues in Canada. *Society and Natural Resources* 30:934–948.

Pienaar, E. F., D. Telesco, and S. Barrett. 2015. Understanding people's willingness to implement measures to manage human-bear conflict in Florida. *Journal of Wildlife Management* 79:798–806.

R Core Team. 2019. R: a language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria.

Revelle, W. 2019. psych: procedures for psychological, psychometric, and personality research. Northwestern University, Evanston, Illinois, USA. R package version 1.9.12. <<https://cran.r-project.org/package=psych>>. Accessed 4 Apr 2020.

Riley, S. J., W. F. Siemer, D. J. Decker, L. H. Carpenter, J. F. Organ, and L. T. Berchielli. 2003. Adaptive impact management: an integrative approach to wildlife management. *Human Dimensions of Wildlife* 8:81–95.

Ripple, W. J., J. A. Estes, R. L. Beschta, C. C. Wilmers, E. G. Ritchie, M. Hebblewhite, J. Berger, B. Elmhagen, M. Letnic, M. P. Nelson, et al. 2014. Status and ecological effects of the world's largest carnivores. *Science* 343:1241484.

Sakurai, R. 2019. Human dimensions of wildlife management in Japan: from Asia to the World. Springer, Singapore.

Sakurai, R., S. K. Jacobson, N. Matsuda, and T. Maruyama. 2015. Assessing the impact of a wildlife education program on Japanese attitudes and behavioral intentions. *Environmental Education Research* 21:542–555.

Salvatori, V., and J. Linnell. 2005. Report on the conservation status and threats for wolf (*Canis lupus*) in Europe. Council of Europe.

Sandler, T. 2015. Collective action: fifty years later. *Public Choice* 164:195–216.

Saypanya, S., T. Hansel, A. Johnson, A. Bianchessi, and B. Sadowsky. 2013. Effectiveness of a social marketing strategy, coupled with law enforcement, to conserve tigers and their prey in Nam Et Phou Louey National Protected Area, Lao. People's Democratic Republic. *Conservation Evidence* 10:57–66.

Sillero-Zubiri, C., R. Sukumar, and A. Treves. 2007. Living with wildlife: the roots of conflict and the solutions. Pages 255–272 in D. Macdonald and K. Service, editors. *Key topics in conservation biology*. Oxford University Press, Oxford, United Kingdom.

Smith, J. W., J. E. Leahy, D. H. Anderson, and M. A. Davenport. 2013. Community/agency trust and public involvement in resource planning. *Society and Natural Resources* 26:452–471.

Stern, M. J., and K. J. Coleman. 2015. The multidimensionality of trust: applications in collaborative natural resource management. *Society and Natural Resources* 28:117–132.

Støen, O.-G., A. Ordiz, V. Sahlén, J. M. Arnemo, S. Sæbo, G. Mattsing, M. Kristofferson, S. Brunberg, J. Kindberg, and J. E. Swenson. 2018. Brown bear (*Ursus arctos*) attacks resulting in human casualties in Scandinavia 1977–2016; management implications and recommendations. *PLoS ONE* 13(5):e0196876.

Treves, A., R. R. Jurewicz, L. Naughton-Treves, R. A. Rose, R. C. Willging, and A. P. Wydeven. 2002. Wolf depredation on domestic animals in Wisconsin, 1976–2000. *Wildlife Society Bulletin* 30:231–241.

Treves, A., and K. U. Karanth. 2003. Human-carnivore conflict and perspectives on carnivore management worldwide. *Conservation Biology* 17:1491–1499.

United States Department of Agriculture [USDA]. 2017. Montana: total and per farm overview, 2017 and change since 2012. United States Department of Agriculture, National Agriculture Statistics Service, Washington, D.C., USA.

United States Department of Agriculture [USDA]. 2019. Program data reports C and G. Program Data Reports. <[https://www.aphis.usda.gov/aphis/ourfocus/wildlifedamage/sa\\_reports/sa\\_pdrs/PDR-Home-2018](https://www.aphis.usda.gov/aphis/ourfocus/wildlifedamage/sa_reports/sa_pdrs/PDR-Home-2018)>. Accessed 10 Feb 2020.

United States Geological Survey. 2018. Gap analysis project. Protected areas database of the United States. <<https://doi.org/10.5066/P955KPLE>>. Accessed 3 Jul 2020.

Vaske, J. J. 2008. Survey research and analysis: applications in parks, recreation, and human dimensions. Venture Publishing, State College, Pennsylvania, USA.

Venables, W. N., and B. D. Ripley. 2002. Modern applied statistics with S. Fourth edition. Springer, New York, New York, USA.

Veríssimo, D., B. Tully, and L. R. Douglas. 2019. Conservation marketing as a tool to promote human-wildlife coexistence. Pages 335–358 in B. Frank, J. A. Glikman, and S. Marchini, editors. *Human-wildlife interactions: turning conflict into coexistence*. Cambridge University Press, Cambridge, United Kingdom.

Wagner, M. W., U. P. Kreuter, R. A. Kaiser, and R. N. Wilkins. 2007. Collective action and social capital of wildlife management associations. *Journal of Wildlife Management* 71:1729–1738.

Weather Atlas. 2021. Monthly weather forecast and climate: Montana, USA. <[https://www.weather-us.com/en/montana-usa-climate#climate\\_text\\_5](https://www.weather-us.com/en/montana-usa-climate#climate_text_5)>. Accessed 21 Jan 2021.

Willcox, A. S., W. M. Giuliano, and M. C. Monroe. 2012. Predicting cattle rancher wildlife management activities: an application of the theory of planned behavior. *Human Dimensions of Wildlife* 17:159–173.

Wilson, S. M., E. H. Bradley, and G. A. Neudecker. 2018. Learning to live with wolves: community-based conservation in the Blackfoot Valley of Montana. *Human-Wildlife Interactions* 12:156–156.

World Population Review. 2020. United States by density 2020. <<https://worldpopulationreview.com/state-rankings/state-densities>>. Accessed 21 Jan 2021.

Yau, Y. 2011. Collectivism and activism in housing management in Hong Kong. *Habitat International* 35:327–334.

Young, H. A. 2018. Effectiveness of promotion or prevention message frames on food storage messages about black bears. Thesis, Colorado State University, Fort Collins, USA.

Yung, L., J. Chandler, and M. Haverhals. 2015. Effective weed management, collective action, and landownership change in western Montana. *Invasive Plant Science and Management* 8:193–202.

Zinn, H. C., M. J. Manfredo, J. J. Vaske, and K. Wittmann. 1998. Using normative beliefs to determine the acceptability of wildlife management actions. *Society and Natural Resources* 11:649–662.

*Associate Editor: Lincoln Larson.*

## SUPPORTING INFORMATION

Additional supporting information may be found in the online version of this article at the publisher's website.