Received: 6 September 2021 | Revised: 1 July 2022 | Accepted: 8 July 2022

DOI: 10.1002/jwmg.22300

RESEARCH ARTICLE

THE JOURNAL OF WILDLIFE MANAGEMENT

THE WILDLIFE SOCIETY

Demographic uncertainty and disease risk influence climate-informed management of an alpine species

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Abstract

Climate change is expected to disproportionately affect species occupying ecosystems with relatively hard boundaries, such as alpine ecosystems. Wildlife managers must identify actions to conserve and manage alpine species into the future, while considering other issues and uncertainties. Climate change and respiratory pathogens associated with widespread pneumonia epidemics in bighorn sheep (*Ovis canadensis*) may negatively affect mountain goat (*Oreamnos americanus*) populations. Mountain goat demographic and population data are challenging to collect and sparsely available, making population management decisions difficult. We developed predictive models incorporating these uncertainties and analyzed results within a structured decision making framework to make management recommendations and identify priority information needs in Montana, USA. We built resource selection models to forecast occupied mountain goat habitat and account for uncertainty in effects of climate change, and a

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Funding information
National Park Service; Montana Fish, Wildlife & Parks; U.S. Forest Service; North Central Climate Adaptation Science Center

Leslie matrix projection model to predict population trends while accounting for uncertainty in population demographics and dynamics. We predicted disease risks while accounting for uncertainty about presence of pneumonia pathogens and risk tolerance for mixing populations during translocations. Our analysis predicted that new introductions would produce more area occupied by mountain goats at mid-century, regardless of the effects of climate change. Population augmentations, carnivore management, and harvest management may improve population trends, although this was associated with considerable uncertainty. Tolerance for risk of disease transmission affected optimal management choices because translocations are expected to increase disease risks for mountain goats and sympatric bighorn sheep. Expected value of information analyses revealed that reducing uncertainty related to population dynamics would affect the optimal choice among management strategies to improve mountain goat trends. Reducing uncertainty related to the presence of pneumonia-associated pathogens and consequences of mixing microbial communities should reduce disease risks if translocations are included in future management strategies. We recommend managers determine tolerance for disease risks associated with translocations that they and constituents are willing to accept. From this, an adaptive management program can be constructed wherein a portfolio of management actions are chosen based on risk tolerance in each population range, combined with the amount that uncertainty is reduced when paired with monitoring, to ultimately improve achievement of fundamental objectives.

KEYWORDS
adaptive management, bighorn sheep, climate change, climate adaptation, mountain goat, *Oreamnos americanus*, *Ovis canadensis*, structured decision making, value of information

Climate change poses significant and complex challenges for wildlife management because it will affect different ecosystems and species in different ways and at different paces (Loarie et al. 2009). Species occupying habitats constrained by hard geographic boundaries, such as alpine areas, are most vulnerable to population decline and extinction (Parmesan 2006). The disproportionate vulnerability of alpine species to climate change effects is consistent across taxa (Dirnböck et al. 2011). Notwithstanding these general assessments and their limited control over global climate trends, wildlife managers must identify present actions to conserve and manage alpine species. This can be difficult given uncertainty in climate change effects at local scales and the multiple other considerations involved in wildlife management decisions.

Scenario planning is a process often used to plan management actions that account for plausible future projections (Kahane 2012) and has been increasingly applied to consider climate change effects in natural resource management (Cobb and Thompson 2012, Rangwala et al. 2021). Such applications can facilitate and promote climate adaptation planning (Magness et al. 2022). But uncertainties and issues unrelated to climate change affect managers' ability to implement approaches designed as climate adaptation strategies (Clifford et al. 2022). Ideally, such non-climate-related uncertainties and issues should be considered concurrently with climate change to design optimal management strategies.

Scientists and managers have raised concerns about the current and future status of mountain goats (*Oreamnos americanus*), a species associated with alpine ecosystems, in recent years (Smith 2014). Despite widespread efforts to reduce direct human impacts such as protection of important habitats and reducing and strictly regulating human harvest (Alberta Sustainable Resource Development 2003, Idaho Department of Fish and Game 2019), many populations across North America are struggling (Smith 2014). Research and monitoring data for mountain goats are generally scarce, resulting in uncertainty about population status and factors affecting population trends (Smith 2014, DeCesare and Smith 2018). Furthermore, multiple factors may negatively influence mountain goat populations simultaneously, including climate change in alpine ecosystems (Pederson et al. 2010, White et al. 2018), disease transmission (Blanchong et al. 2018), and restored predator populations (Festa-Bianchet et al. 1994, Lehman et al. 2020).

Amongst the range of climate projections and associated uncertainty lies a distinct possibility that climate change may impose new limits to mountain goat distribution. For example, climate change is predicted to cause large-scale range declines and extirpation of populations in southeastern Alaska, USA, through loss of alpine habitats (White and Gregovich 2017, White et al. 2018). High summer temperatures reduced mountain goat survival in southeastern Alaska, and population declines are predicted to occur under various climate change scenarios (White et al. 2011, 2018). Mountain goats in Glacier National Park in Montana, USA, use snow to slow respiration during summer (Sarmento et al. 2019). Results from individual study areas, however, do not always extrapolate reliably to different ecological conditions or to larger-scale management strategies encompassing a range of conditions (Morrison 2012, Hiers et al. 2016). The existence of populations in warmer and drier regions (e.g., the Black Hills, SD, USA, several populations in NV, USA) also suggests that climate change may not strictly limit the distribution of mountain goat populations into the future.

Data on mountain goat demography and population dynamics are extremely limited. Researchers have conducted long-term studies estimating vital rates, demographics, and population dynamics in southeastern Alaska (Smith 1986; White et al. 2011, 2018, 2021) and west-central Alberta, Canada (Festa-Bianchet et al. 1994, Hamel et al. 2006, Festa-Bianchet and Côté 2008, Côté and Hamel 2018). Vital rate data derived from individually marked mountain goats are sparse or non-existent in most other jurisdictions. Population surveys are also relatively rare and inconsistent (DeCesare and Smith 2018). Accordingly, the best information on population status and trends generally comes from the expertise of local biologists responsible for managing each population.

Managers established mountain goat populations in many areas outside of their historical range during the twentieth century (Smith 2014), with possible negative impacts on native communities. Introduced mountain goats negatively affected native alpine plant communities in Olympic National Park in Washington, USA (Houston et al. 1994), but did not appear to affect plant community composition or vegetation cover in Yellowstone National Park in Wyoming and Montana, USA (Aho 2012). Demonstrating the potential for resource competition with sympatric bighorn sheep (*Ovis canadensis*) in the Greater Yellowstone Ecosystem, DeVoe et al. (2015) reported a wide distribution of introduced mountain goats with additional potential unoccupied habitat, and Flesch et al. (2016) reported substantial recent mountain goat population growth and range expansion. Although both species have overlapping niches in the Greater Yellowstone Ecosystem (Lowrey et al. 2018*b*), bighorn sheep population growth was not negatively influenced by sympatry with mountain goats, indicating that competition has not resulted in population-level effects (Flesch and Garrott 2013).

Beyond the potential for resource competition, sympatry with bighorn sheep may also induce spillover of respiratory pathogens (Kamath et al. 2019). Mountain goats and bighorn sheep harbor respiratory pathogen communities associated with widespread, epidemic die-off events in bighorn sheep (Cassirer et al. 2018, Lowrey et al. 2018*a*, Kamath et al. 2019). These respiratory pathogens may also cause epidemics in mountain goats (Blanchong et al. 2018, Wolff et al. 2019). Sharing of respiratory pathogens between sympatric mountain goat and bighorn sheep populations is a central concern regarding mountain goat management in many areas. Little is known about mountain goat respiratory pathogen communities or their effects in most areas because population monitoring has been limited.

Given these uncertainties in the effects of climate change, demography, and respiratory pathogens, decisions to improve mountain goat management are tough. Decision analysis provides a means to explicitly account for uncertainty in decision-making (Keeney 1982, Keeney and Raiffa 1993). Decision analysis provides a framework to integrate scientific knowledge related to climate change with other scientific knowledge relevant to other objectives into a cohesive, policy-relevant package (Martin et al. 2011). The utility of decision analysis includes identification of optimal management approaches with respect to management objectives and current knowledge, and identification of information needed to improve future decisions (Conroy and Peterson 2013).

We used predictive models and value of information analyses to develop proactive recommendations to improve the distribution and demographics of mountain goats in Montana. Using a decision framework provided by mountain goat population and habitat managers, our specific objectives were to make recommendations regarding optimal management strategies based on predictions incorporating uncertainty and risk tolerance and to analyze the value of information to prioritize research and monitoring needs. We considered uncertainty in climate change, demographics, and disease at a statewide scale. To represent uncertainty in climate change effects, we used alternative hypotheses representing that climate change will or will not limit the future distribution of mountain goats, and we incorporated variation in projections from multiple climate models. We simulated population dynamics incorporating uncertainty in starting population sizes, age-sex structures, and vital rates based on the limited, available information. We used 3 hypotheses to bracket the range of uncertainty in which populations carry pneumonia-associated pathogens: 1) only populations currently known to harbor the pathogens, 2) all populations, or 3) populations with historical or current range overlap with domestic sheep. We also used expert elicitation to estimate the relative risk and risk tolerance for mixing pathogen communities of mountain goats and bighorn sheep during translocations. We then estimated the extent to which reducing each type of uncertainty would improve achievement of mountain goat management objectives and thereby recommend priority information needs that are directly tied to mountain goat management success at the large scale we considered.

STUDY AREA

Our study area was the 229,000-km^2 area of Montana Fish, Wildlife & Parks (FWP) administrative regions 1–5, which encompassed all 58 extant mountain goat populations in Montana during 2018–2020 (Figure 1). We defined mountain goat populations in accordance with spatial boundaries of hunting districts, national parks, Indian reservations, or other administrative boundaries distinguishing areas occupied by mountain goats. Mountain goat distribution is marked by rugged, rocky topography, primarily in mountainous terrain near the alpine zone. Elevations within mountain goat distribution range from 554–3,878 m and weather is seasonal. During January (winter), mean temperatures range from −14°C to −2°C and precipitation falls primarily as snow. During July (summer) mean temperatures range from 6–23°C and precipitation falls primarily as rain. Land use varies and includes primarily public lands, though some mountain goat populations overlap private lands. Alpine flora includes ericaceous shrubs such as western moss heather (*Cassiope mertensiana*), white arctic mountainheather (*Cassiope tetragona*), yellow mountain heath (*Phyllodoce glanduliflora*), pink mountain heath (*Phyllodoce empetrifomis*), and alpine bog laurel (*Kalmia microphylla*), and mat-forming or dwarf-shrub alpine willows (*Salix* spp.). The herbaceous understory is composed of a diversity of alpine sedges (*Carex* spp.), rushes (*Juncus* spp.), woodrushes (*Luzula* spp.), and alpine grasses and forbs. Subalpine forests are dominated by spruce (*Picea* spp.) and fir (*Abies* spp.) trees.

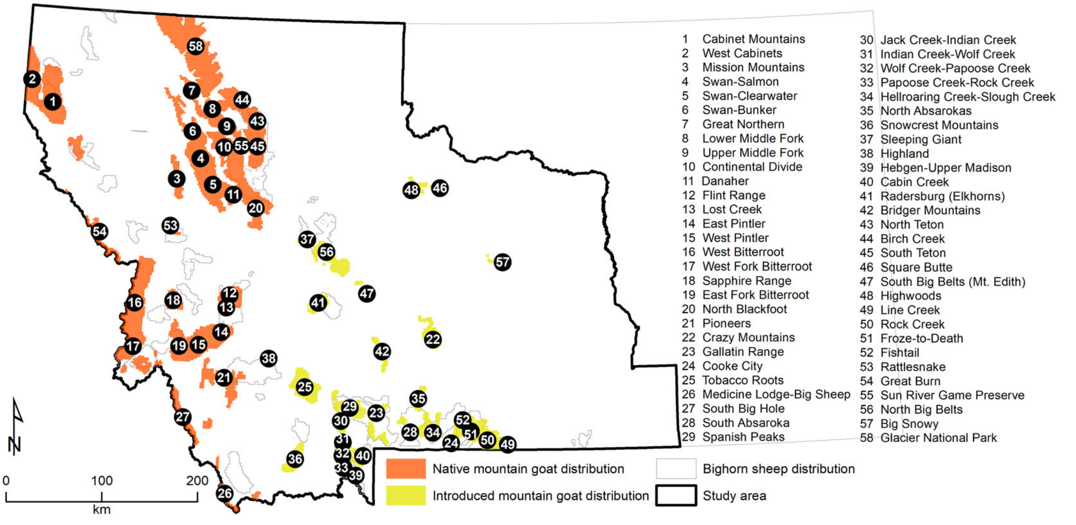

FIGURE 1 Mountain goat distribution in Montana, USA, 2018, divided into 58 populations in native and introduced ranges within the study area boundary, and bighorn sheep distribution within the study area.

Sympatric ungulates include elk (*Cervus canadensis*), white-tailed deer (*Odocoileus virginianus*), mule deer (*O. hemionus*), bighorn sheep, and moose (*Alces alces*). Large carnivores include mountain lions (*Puma concolor*), wolves (*Canis lupus*), grizzly bears (*Ursus arctos*) and black bears (*U. americanus*). Mountain goat populations are also sympatric with bald (*Haliaeetus leucocephalus*) and golden eagles (*Aquila chrysaetos*). By 2017, mountain goat abundance within their native range was approximately 25% of that estimated during the 1940s (DeCesare and Smith 2018). Populations introduced by FWP outside of their native range beginning in the 1940s were largely prospering, with some exceptions (DeCesare and Smith 2018).

METHODS

Decision framework

A group of professional staff from federal and state agencies with responsibilities for mountain goat management used a structured decision making (SDM) process to outline a decision framework. Structured decision making is a value-focused formalization of common sense, designed to ensure that all components of a decision are thoroughly considered in complex situations (Keeney 1982). The decision framework included fundamental objectives for mountain goat management and a set of alternative management strategies (AMS; Gude et al. 2020). Because 4 fundamental objectives were associated with considerable uncertainty, we developed a modeling process to predict effects of AMS on fundamental objectives and analyzed how uncertainty influenced decisions among AMS (Figure 2).

The working group identified 6 fundamental objectives. These were to maximize the number of mountain goat population units that were 1) occupied and 2) meeting population trend objectives; to minimize disease risks to 3) bighorn sheep and 4) mountain goats; and to minimize 5) costs and 6) social conflicts resulting from mountain goat management. Our modeling and analyses were focused on the first 4 objectives for which there was considerable scientific uncertainty, and we describe the details of these objectives and our prediction process subsequently. Our complete decision analysis considered all 6 objectives. Gude et al. (2020) provide details about objectives 5 and 6 and the associated tradeoffs.

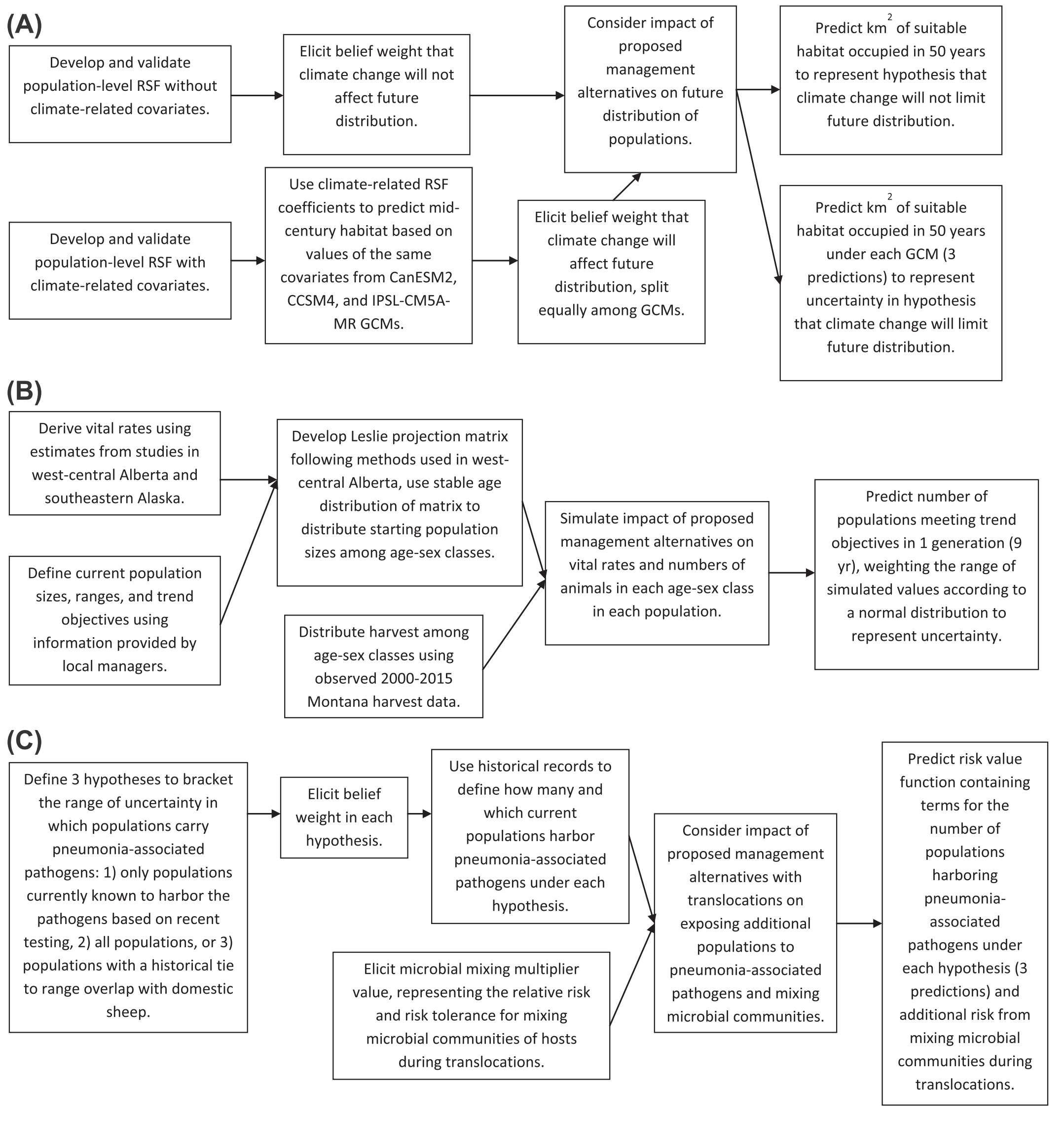

FIGURE 2 Process flow for including uncertainty in predictive modeling for mountain goats in Montana, USA, 2020, for use in decision analysis of A) the amount of suitable habitat that will be occupied at mid-century (2040–2069), where RSF refers to resource selection function and GCM refers to global climate model, B) the number of mountain goat populations that will meet trend objectives in 1 generation, and C) risk value function for the number of bighorn sheep and mountain goat populations exposed to pneumonia-related pathogens.

The decision framework included 7 AMS identified for mountain goat management in Montana (Gude et al. 2020), which we used as the basis for predicting future distribution, population trends, and disease risk: 1) status quo AMS (monitor populations and employ conservative harvest management; detailed in DeCesare and Smith 2018); 2) top-down mortality AMS (restrict mortality from harvest and reduce predation from carnivores); 3) introduction AMS (translocate mountain goats into currently unoccupied areas); 4) augmentation AMS (conduct augmentations into small, struggling, or declining mountain goat populations); 5) habitat protection AMS (protect seasonal mountain goat habitats from human use); 6) combined AMS with augmentations (combination of actions from the above alternatives based on their predicted performance at achieving fundamental objectives); and 7) combined AMS without augmentations (alternative 6 but omitting augmentations).

Predictions and uncertainty

Area of occupied mountain goat habitat

We predicted the area of suitable habitat occupied by mountain goat populations in the next 50 years as a measure of fundamental objective 1. The time horizon of 50 years balanced uncertainty in future predictions and the long time horizon for climate change. Mid-century (2040–2069) climate projections are also common outputs in many global climate models (GCMs). Our predictions incorporated output from multiple GCMs to quantify uncertainty in effects of climate change on future mountain goat habitat.

We developed population-level resource selection functions (RSFs) with a used-unused design to predict the probability of supporting mountain goat populations across western and central Montana (Manly et al. 2002). We sampled 10,000 random points within current mountain goat distribution (Figure 1) to reflect used conditions, and 100,000 random points throughout the rest of our study area to represent unused conditions.

To represent uncertainty about effects of climate change on mountain goat distribution in 50 years, we fit RSFs with and without climate-related covariates. We made 4 sets of predictions representing 4 alternative hypotheses about the area that will be occupied in 50 years under each AMS. The RSF without climate-related covariates represented the hypothesis that climate change will not alter mountain goat habitat. Using mid-century spatial projections from 3 GCMs (the second generation Canadian Earth System Model [CanESM2], a Community Climate System Model [CCSM4], and an Institut Pierre Simon Laplace Model [IPSL-CM5A-MR]) and the RSF with climate-related covariates, we forecasted 3 alternative hypotheses wherein mid-century temperature and precipitation conditions for the Pacific Northwest were very hot and very wet (CanESM2), hot and very dry (CCSM4), and very hot and wet (IPSL-CM5A-MR). These 3 GCMs accurately represent the historical climate of the Rocky Mountains and Pacific Northwest (Rupp et al. 2013). We considered the GCM projections based on representative concentration pathway (RCP) 8.5 for greenhouse gas emissions, which represents the high carbon emissions scenario into the future. Our primary rationale for solely considering RCP 8.5 was to maximize the contrast between the climate-related RSF model and the non-climate-related RSF. Also, projected mid-century climate responses are less sensitive to the choice of emission scenario than late-century responses (Rangwala et al. 2021), and RCP 8.5 is correlated with recent emission trends and with stated policy goals through mid-century (Schwalm et al. 2020).

To build the RSFs, we resampled all covariates to a 300-m^2 resolution because of the large scale of inference about the future distribution of mountain goat populations. Covariates included elevation, slope, slope variance, canopy cover, cumulative winter snow water equivalent (SWE; climate-related covariate), precipitation (climate-related covariate), growing degree days (climate-related covariate), mean winter temperature (Dec, Jan, and Feb; climate-related covariate), and potential vegetation type (climate-related covariate), all of which we hypothesized would affect mountain goat distribution. We used a digital elevation model (DEM) from the U.S. Geological Survey 3D Elevation Program (U.S. Geological Survey 2019) to depict elevation at 30-m resolution and estimated slope and slope variance (estimated from 30-m pixels, then averaged over 300 m) from this DEM using the raster package in R (Hijmans et al. 2015). We used the percent tree canopy layer from the 2011 National Land Cover Database (Homer et al. 2015) and characterized SWE using the Snow Data Assimilation System (SNODAS; National Operational Hydrologic Remote Sensing Center 2004). To build the climate-related RSF, we used 4-km gridMET layers representing 1971–2000 annual precipitation, growing degree days, and winter temperature (Abatzoglou 2013; climatologylab.org/gridmet.html, accessed 26 Jul 2022) and potential vegetation type based on the Mapped Atmosphere-Plant-Soil System Century 2 Dynamic Global Vegetation Model (Sheehan et al. 2015; databasin.org/galleries/18202c2bb41f4b0ab9b6ddd3a4531ef8/, accessed 26 Jul 2022). For mid-century predictions based on the climate-related RSF, we used layers representing 2040–2069 forecasts for precipitation, growing degree days, and winter temperature from the 3 GCMs downscaled to the 4-km gridMET resolution using the multivariate adaptive constructed analogs method (Abatzoglou and Brown 2012; climatologylab.org/maca.html, accessed 26 Jul 2022) and potential vegetation types under the no fire suppression scenario (Sheehan et al. 2015), which we collapsed to forest, alpine tundra, and other categories.

We began analyses with univariate regressions for each covariate and assessment of correlations between covariates. In cases of covariates with correlation coefficients >0.6, we removed one from further consideration according to univariate significance. We also used univariate results to detect issues of multicollinearity (sign-switching or variance inflation) in subsequent multivariable models. We then used a manual, backward-stepping model selection procedure to identify a best model for non-climate-related and climate-related scenarios. Lastly, we added quadratic functional forms to all continuous covariates to assess if they improved models over those with only linear terms. We fit the RSF models using logistic regression and standardized covariates in R (R Core Team 2020). We chose the top non-climate-related and climate-related model using the Akaike Information Criterion (AIC). We incorporated uncertainty using predictions from the top non-climate-related RSF and the top climate-related RSF, incorporating 3 forecasts from separate GCMs in the latter, rather than using multi-model inference based on AIC results. We validated predictive accuracy of top models using k-folds cross-validation, withholding 5 partitions of data and assessing the correlation between model predictions and the frequency of used locations.

We next predicted the area (km^2) of suitable habitat that will be occupied in 50 years in each population under each AMS. To do so, we discretized continuous RSF predictions into categorical delineations of suitable habitat. We compared categorical bins of RSF predicted values to frequency of used locations tallied within each bin to identify thresholds of occupied and unoccupied habitats. We divided predictions from current-year RSF models into 10 equal-area bins, grouped into values representing suitable (bins 9 and 10; encompassing 20% of the study area containing the top 20% of available predicted RSF values), marginal (bins 6–8), and non-habitat (bins 1–5). Bins 9 and 10 contained 85.0% of the used locations sampled from the current mountain goat distribution layer for the top climate-related RSF model. We applied the same threshold values used to delineate suitable and marginal habitat categories under current conditions to the 4 sets of predictions (i.e., from the top non-climate-related RSF and the top climate-related RSF incorporating forecasts from the 3 GCMs) characterizing habitat conditions 50 years into the future.

Lastly, we intersected suitable habitat predictions with boundaries of existing mountain goat distribution (Figure 1) to identify which subset of suitable habitat was occupied under both present and future scenarios. We did not forecast changes in occupied boundaries themselves and assumed any suitable habitat within currently occupied regions would remain occupied. We reclassified patches of unoccupied but suitable habitat as occupied under AMS that included introductions into those areas.

Mountain goat population trends

We predicted how many mountain goat populations would meet trend objectives 1 generation (9 yr; Hamel et al. 2009) from 2020 for fundamental objective 2. We chose this metric to value all populations equally rather than aggregating a statewide population trend or focusing on struggling populations. Only 10 populations include >100 individuals, and these populations encompass roughly 65% of the mountain goats in Montana, while struggling populations are disproportionately within native range (DeCesare and Smith 2018). Predicting overall population trend would have highlighted management actions that bolster the largest populations, whereas focusing on struggling populations would have highlighted management actions in native herds; both options were inconsistent with our intent. Wildlife biologists responsible for managing each population derived trend objectives (increasing, stable, or declining) subjectively based on their local knowledge and experience, considering habitat, space limitations in each population, and historical and recent survey records. We used mean generation time to balance the need for reasonable precision with the length of time required for management actions to influence population dynamics (Festa-Bianchet and Côté 2008). We incorporated uncertainty in starting population sizes, vital rates, starting population age structures, and the age structure of mountain goats harvested by hunters.

We based starting population sizes on DeCesare and Smith (2018), who solicited expert opinion from local wildlife biologists for all mountain goat populations across Montana. This provided population point estimates, range of confidence intervals for each estimate, and recent population trends (2010–2015; increasing, stable, or declining). We randomly drew starting population sizes from these range of confidence intervals as inputs into stochastic population simulations.

To simulate uncertainty in mountain goat vital rates, we built a 2-sex, 17-stage (i.e., 34 stage) post-birth Leslie matrix population model (Caswell 2001), following the matrix modeling methods of Hamel et al. (2006) and Côté and Hamel (2018; Figure A1, available in Supporting Information). We relied primarily on vital rate data collected via long-term study in Alberta (Festa-Bianchet and Côté 2008) because there was a lack of similar data in Montana. We derived adult female survival, age-specific fecundity, and kid survival by dividing these key vital rates into time periods representing 3 trend scenarios (decreasing, stable, or increasing) observed during that study (Table 1). We assumed a 50:50 sex ratio of newborns. We derived remaining vital rates from studies in Alberta and Alaska (Hamel et al. 2006, White et al. 2011, Côté and Hamel 2018), primarily as proportions of adult female survival and fecundity (Table A1, available in Supporting Information) to induce covariance in vital rates during simulation iterations.

We ran 1,000 stochastic simulations for each AMS using R packages popbio (Stubben and Milligan 2007) and rramas (de la Cruz 2019). Simulations included the 58 current mountain goat populations plus any new populations introduced during an AMS. We drew values from a beta distribution for key vital rates (Table 1) and adjusted other vital rates accordingly. For each population and simulation iteration, we randomly distributed starting population sizes among age- and sex-specific population vectors according to the stable age distribution of the simulated Leslie matrix.

To simulate effects of harvest on population dynamics, we used 2019 mountain goat hunting license quotas for hunting districts with open seasons, multiplied by the observed 72% average hunter success rate during 2000–2015. We adjusted quotas accordingly for each AMS considered. Because hunting licenses in Montana are generally not age or sex specific, during simulations we drew the sex and age of each harvested individual randomly

TABLE 1 Vital rate scenarios ($\bar{x}$ and 95% CI) for adult females and newborns used to represent declining, stable, increasing, and uncertain population trends in the Leslie matrix population model for mountain goats in Montana, USA, 2020. We derived these vital rates from the Caw Ridge population in Alberta, Canada (Hamel et al. 2006, Côté and Hamel 2018) during time periods when the Caw Ridge population was declining (2004–2017), stable (1993–2017), and increasing (1993–2003). Because vital rates during the 1993–2017 period led to asymptotic lambda slightly <1, we increased adult female survival, newborn survival, and adult female fecundity in proportion to their relative variation in the data (by 2%, 8%, and 18%, respectively) such that asymptotic lambda = 1.00. We created the uncertain category for these vital rates using the point estimates from the stable population category but with larger confidence intervals that fully spanned the range of values from all categories, including declining to increasing values.

	Adult female survival		Newborn survival		Adult female fecundity	
	$\bar{x}$	95% CI	$\bar{x}$	95% CI	$\bar{x}$	95% CI
Declining	0.87	0.85, 0.90	0.48	0.39, 0.56	0.56	0.47, 0.66
Stable	0.92	0.89, 0.95	0.59	0.48, 0.70	0.67	0.58, 0.76
Increasing	0.94	0.90, 0.99	0.62	0.49, 0.75	0.75	0.65, 0.85
Uncertain	0.92	0.85, 0.99	0.59	0.39, 0.75	0.67	0.30, 0.85

based on the age-sex distribution of observed 2000–2015 harvests (65% male, 35% female, 33% age <4, 67% age ≥4; Gude et al. 2020: table 7).

In simulations for the top-down mortality AMS, we removed all simulated hunter harvest from mountain goat populations not currently meeting or exceeding trend objectives. We also included a prescription of increased harvest of carnivores, which we assumed would increase kid survival, because this is the primary vital rate affected by carnivores in Alberta (Festa-Bianchet et al. 1994). For these simulations, we therefore increased kid survival to the mean and variance values for increasing populations (Table 1).

In simulations of AMS involving mountain goat translocations (the introduction, augmentation, and combined AMS), we increased starting population size in the recipient populations and decreased starting population size in the source populations. For source populations, we set harvest quotas to 0 for 9 years, thereby replacing harvest mortality with translocation removals. When animals were translocated for introduction or augmentation, we changed vital rates for the recipient population to the uncertain trend scenario (Table 1), centered around a stable population trend but with the largest amount of uncertainty.

Under simulations for the habitat protection AMS, we assumed this would increase fecundity of adult females. We expected that human disturbance would manifest demographically in reduced nutritional reserves or increased stress due to reductions in foraging, increases in energy use, and shifts in habitat use or distribution (Northern Wild Sheep and Goat Council 2020). Mountain goats have relatively constant adult survival but greater annual variation in reproductive success (Festa-Bianchet and Côté 2008), suggesting that reduced nutritional reserves or increased stress are most likely to influence reproductive success. For example, female reproduction is sensitive to costs faced the year prior, such as reproductive effort or high population density (Hamel et al. 2009). Because predation or captures have been linked to stress-induced declines in fecundity (Côté et al. 1998, Dulude-de Broin et al. 2020), we assumed this was the likely pathway between such a management action and a demographic outcome. Accordingly, populations assigned habitat protection were assigned the fecundity values from the increasing trend scenario.

We used the final population size for each simulation to assess whether each population was increasing (≥20% higher than 2020, corresponding to a 2% annual increase), decreasing (≥20% lower, corresponding to a 2% annual decrease), or stable (<20% higher or lower) in 1 generation. We chose the relatively large threshold of 20% change to reflect the wide variation in annual count data, which makes annual population rates of change <2% difficult to estimate (DeCesare and Smith 2018). To represent variability, we weighted distributions of simulation results for each population approximately normally. We placed weights of 0.45 on median simulated values, 0.25 on lower and upper quartiles, and 0.025 on the lower and upper 2.5% of values for each population. We then calculated an expected value prediction for the number of mountain goat populations achieving trend objectives 1 generation from 2020 under each AMS as the weighted mean of this distribution.

Disease risks to mountain goat and bighorn sheep populations

We measured performance of fundamental objectives 3 and 4 using a value function for the number of bighorn sheep or mountain goat herds with pathogen transmission risks, respectively, at present or following management actions. The causes of respiratory disease in alpine ungulates are likely polymicrobial or strain-specific (Cassirer et al. 2017, 2018), and mixing microbial communities during translocations may initiate a pneumonia epidemic. Our risk value function represented risk associated with pneumonia outbreaks arising from pathogen presence or mixing, notwithstanding other factors that may affect disease expression (Gullis and Fujino 2015, Sells et al. 2015, Butler et al. 2018):

$$\text{Risk value} = KP + (M \times NM),$$

where KP was the predicted number of populations (either species) harboring pneumonia-associated pathogens, NM was the number of populations mixed through translocations under each AMS, and M was an expression of risk tolerance for uncertainty surrounding consequences of mixing pathogens through translocations. The predicted number of populations harboring pneumonia-associated pathogens varied among hypotheses representing uncertainty about the number of populations with pathogens (see below), and both *KP* and *NM* varied among AMS because some involved translocations that would mix populations. Risk tolerance is an individual, value-based attribute that must be accounted for in decision-making (Goodwin and Wright 2014). A value of $M = 0$ reflects that translocations into struggling populations or new areas do not pose additional risk beyond the existing pathogen presence alone. Values of $0 < M < 1$ represent fractional increases in disease epidemic risks compared to pneumonia pathogen presence. If $M = 1$, mixing pathogen communities during translocations poses an additive risk equally weighted to the existing epidemic risk, essentially doubling the risk in scenarios where pathogens from a source population add to an already infected recipient herd. Values of $M > 1$ represent multiplicative increases such that mixing of pathogens induced a synergistic risk greater than that posed by a simple additive effect of exposure to multiple pathogen sources.

Considerable uncertainty exists about pathogen communities of bighorn sheep populations and particularly of mountain goat populations in Montana. We characterized disease risk for each AMS by considering inter-species range overlap, limited pathogen testing data, and translocations. We quantified risk for 29 extant populations of bighorn sheep that overlap mountain goat herds, 58 extant populations of mountain goats, and up to 5 additional mountain goat populations (as specified by each AMS). At the time of analysis, 1 population of bighorn sheep was sympatric with a mountain goat population that was known to carry pneumonia-associated pathogens, while 24 mountain goat populations were sympatric with bighorn sheep that were known to carry pneumonia-associated pathogens (Almberg et al. 2016, 2018, 2019). Therefore, 1–29 bighorn sheep populations were exposed to pneumonia-associated pathogens from mountain goats, and 24–58 mountain goat populations were currently harboring or exposed to pathogens from bighorn sheep. Translocations under AMS affect these numbers by changing patterns of sympatry and increasing exposure to pneumonia-associated pathogens by moving purported source herds.

We considered 3 hypotheses to capture uncertainty about the number of bighorn sheep and mountain goat populations with pneumonia-associated pathogens. Under the first hypothesis, populations currently known to carry pneumonia-associated pathogens were the only cases in Montana. Under our second hypothesis, all populations in Montana carried such pathogens. Our third hypothesis was that populations with pathogens were those that had current or historical range overlap with domestic sheep or indirect exposure due to translocations of mountain goats or bighorn sheep from ranges that overlapped domestic sheep. This hypothesis was based on the possibility that large-scale declines in bighorn sheep populations in recent centuries may be due to pathogens introduced by domestic sheep (Cassirer et al. 2018). We used historical records of mountain goat ranges, mountain goat transplants, and bighorn sheep transplants (Picton and Lonner 2008) along with knowledge of the historical distribution of domestic sheep grazing areas to generate predictions for this hypothesis.

Elicitation of weights and values

Incorporating uncertainty represented by multiple models requires model weights for multi-model inference (Conroy and Peterson 2013). We elicited belief weights (*B*) for the 2 RSF models and the 3 models for populations with pneumonia-associated pathogens. We elicited *B* using a likelihood point method. For each model set, working group participants distributed 100 points based on belief that a model represented reality. We scaled these values to 0–1 to obtain relative probability weights. The standard practice in scenario planning for climate change is to equally incorporate projections from multiple GCMs, emphasizing plausibility and divergence in future possibilities without assigning relative likelihoods to each scenario (Rangwala et al. 2021, Miller et al. 2022). We therefore split *B* for the climate-related RSF model equally among the 3 forecasts stemming from the divergent GCMs.

We elicited values of *M* (risk tolerance) from wildlife biologists responsible for bighorn sheep and mountain goat management, FWP wildlife health program staff, and academic collaborators with expertise in disease ecology and veterinary science. We provided participants reference values defining meanings of *M* to aid in determining their choice.

We used a modified Delphi method to finalize *B* and *M* (Clark et al. 2006), whereby after completing each exercise, participants were shown results, discussed differences and rationales, and were given the opportunity to change their individual values. We used the mean *B* for each model to represent the belief weight in that model. We calculated expected value predictions of the effect of each AMS on occupied mountain goat habitat and disease risks as weighted means of individual model predictions using *B*. We used the mean, minimum, and maximum *M* value to predict effects of each AMS on disease risk.

Value of information analyses

To determine the relevance of uncertainty related to mountain goat distribution, population trends, and disease risks to identifying the optimal AMS, we used Microsoft Excel to calculate the expected value of perfect information (EVPI; Canessa et al. 2015, Bolam et al. 2019). The EVPI is the difference between the expected value of the outcome if all uncertainty could be eliminated (the first term) and under continued uncertainty (the second term):

$$EVPI = EV_{certainty} - EV_{uncertainty}$$

$$= \mathbb{E}_s[max._a\, V(a, s)] - max._a\, \mathbb{E}_s[V(a, s)]$$

$$= \sum_{s=1}^{N} [\{max._a\, V(a, s)\} \times p_s] - max._a \sum_{s=1}^{N} \{V(a, s) \times p_s\},$$

where $V(a, s)$ refers to the predicted outcome for management alternative *a* under model *s*. Summations occur over *N* models for the metric being predicted and are weighted by the respective probability (p_s) of each model being true. The EVPI is calculated by predicting the expected value of the best AMS conditional on each model being true, calculating the weighted sum of those values using weights for the respective models, then subtracting the expected value of the best AMS under model uncertainty. In our case, model weights were the elicited *B* values for RSF and disease pathogen models and the weighted normal distribution for population simulations. We calculated EVPI separately for predictive models representing each objective because the relative importance of each fundamental objective varied widely among working group members. As our predictive models were general and required many assumptions, we used EVPI > 0 as a threshold to identify priority information needs.

RESULTS

Area of occupied mountain goat habitat

Three covariates (elevation, SWE, and winter temperature) were excluded from final habitat models because they were highly correlated (>0.6) with other covariates while having lower support in univariate models. The top non-climate-related RSF included canopy cover (quadratic form) and slope (quadratic form), whereas the top climate-related RSF model included canopy cover (quadratic form), slope (quadratic form), precipitation (quadratic form), growing degree days (quadratic form), and potential vegetation (Table 2; Table A2, available in Supporting Information). In both models, used locations were consistently located in areas predicted to be in higher quality habitat, and 5-fold cross-validation revealed significant alignment between predictions and used locations (Spearman rho = 0.99, $P < 0.001$ for both models).

We used these models to produce 4 predictions representing the range of uncertainty about how climate change will limit the distribution of mountain goat populations in 50 years (Figure 3). Elicitation from the working

TABLE 2 Standardized coefficient and standard error (SE) estimates from the top non-climate-related and climate-related second-order (population level) resource selection function (RSF) models for mountain goats in Montana, USA, 2018. We used these RSF models to make separate predictions of mountain goat habitat in Montana in 50 years, representing hypotheses that climate change will not or will affect mountain goat habitat, respectively. We made predictions from the top climate-related RSF using mid-century forecasts from 3 different global climate models representing a range of future precipitation, growing degree days, and potential vegetation conditions. The reference category for potential vegetation type included all types other than forest and tundra.

	Top non-climate-related RSF		Top climate-related RSF	
Coefficient	**Estimate**	**SE**	**Estimate**	**SE**
Intercept	−2.901	0.021	−4.118	0.052
Canopy cover	0.465	0.026	0.068	0.032
Canopy cover^2	−0.233	0.015	−0.177	0.017
Slope	1.408	0.028	0.847	0.062
Slope^2	−0.094	0.011	−0.001	0.0002
Precipitation			0.940	0.038
Precipitation^2			−0.050	0.010
Growing degree days			−0.884	0.052
Growing degree days^2			0.141	0.024
Potential vegetation: forest			0.442	0.058
Potential vegetation: tundra			0.128	0.128

group resulted in *B* (belief weights) values of 0.39 on the non-climate-related RSF model and 0.61 on the climate-related RSF model. Splitting 0.61 among predictions from each of the 3 GCM projections yielded *B* values of 0.204. Across AMS, predictions from these 4 models varied by 5,722 km^2 of suitable, occupied habitat by mid-century, or 33% of the predicted 17,283 km^2 of suitable, occupied habitat under the status quo AMS without climate change effects. Specific predictions ranged from a 13% increase in suitable, occupied habitat under the introduction AMS without climate change effects, to a 21% decrease under the status quo AMS with climate change effects and the IPSL-CM5A-MR GCM, compared to the prediction under the status quo AMS without climate change effects (Table 3). We predicted that the introduction AMS would result in more area occupied under every model considered, followed by the combined AMS (with and without augmentations).

Mountain goat population trends

Predictions of the number of mountain goat populations meeting trend objectives in 1 generation varied among AMS (Table 4). We predicted that either the augmentation or combined AMS with augmentations would maximize the number of populations meeting trend objectives, followed by the introduction or top-down mortality AMS. We found substantial variation in predictions, with interquartile ranges of predictions within each AMS differing by an average of 17 populations.

Disease risks to mountain goats and bighorn sheep populations

Historical records and knowledge of mountain goat ranges, mountain goat transplants, bighorn sheep transplants, and domestic sheep grazing areas revealed little difference between our second (all populations carried pathogens)

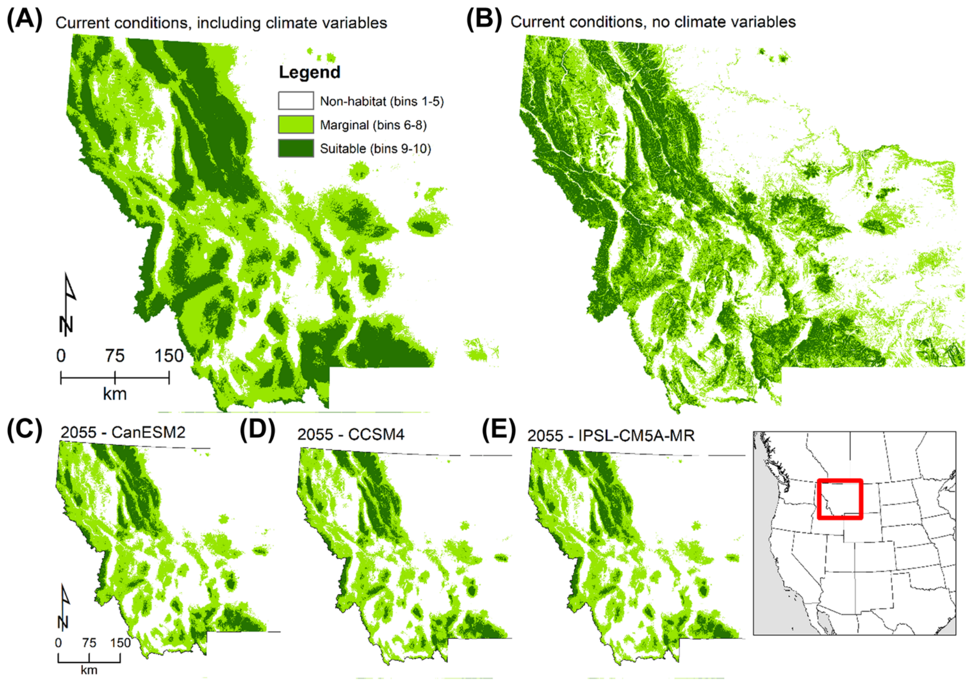

FIGURE 3 Maps depicting the top non-climate-related and climate-related resource selection function (RSF) models for habitat that can support mountain goat populations based on conditions in 2018 (panels A and B), and predictions for habitat that can support mountain goat populations based on incorporating mid-century forecasts (2040–2069) from 3 global climate models (GCMs) into the top climate-related RSF model (C–E) in Montana, USA. We divided RSF models into 10 equal-area bins, and we grouped these bins into values representing suitable (dark green), marginal (light green), and non-habitat (white). For decision analysis incorporating uncertainty about if and how climate change will affect mountain goat habitat, we used the top non-climate-related RSF (B) and the 3 alternative predictions representing possible climate change effects (C–E).

and third hypotheses (history of overlap with domestic sheep) regarding numbers of populations with pneumonia-associated pathogens. All 29 mountain goat populations currently overlapping bighorn sheep, all but 2 existing mountain goat populations, and all purported source populations for translocations historically had range overlap with domestic sheep.

Elicitation resulted in *B* of 0.04 on the model indicating that mountain goat or bighorn sheep populations currently known to harbor pneumonia-associated pathogens are the only such cases, *B* of 0.50 on the model indicating that all populations carry pathogens, and *B* of 0.46 on the model indicating that populations with a historical tie to range overlap with domestic sheep carry pathogens. Elicitation revealed a 0–3 range for *M*, with a mean of 1.6.

The AMS without mountain goat translocations resulted in the lowest predicted numbers of bighorn sheep populations exposed to pneumonia-associated pathogens from mountain goat populations, and vice versa, under every hypothesis (Table 5). At *M* of 1.6 and 3, AMS involving augmentations were riskiest, while at $M = 0$, AMS involving new population introductions were riskier than AMS with augmentations (Table 5).

Value of information analyses

Uncertainty about effects of climate change on the future distribution of mountain goat populations had a large effect on the predicted suitable habitat occupied by mountain goats in 50 years (Table 3). Compared to models with

TABLE 3 Predicted area (km^2) of suitable habitat occupied by mountain goat populations in Montana, USA, in 50 years under alternative predictive models and management strategies. Model predictions are from the top non-climate-related resource selection function (RSF), and the top climate-related RSF, combined with mid-century (2040–2069) spatial forecasts from 3 global climate models (GCM). We elicited model belief weights from biologists and land managers. Expected values are weighted means (using the model belief weights) of model predictions. Alternative strategies focused on population monitoring and conservative harvest management (status quo), restricting mortality from harvest and predation from carnivores (top-down mortality management), translocating mountain goats into currently unoccupied areas (introduction), augmenting small, struggling, or declining populations (augmentation), protecting seasonal habitats from human use (habitat protection), and combined actions from above strategies with or without augmentations (combined with augmentations and combined, no augmentations).

Model	Belief weight	Status quo	Mortality management	Introduction	Augmentation	Habitat protection	Combined with augmentations	Combined, no augmentations
Non-climate-related RSF	0.389	17,283	17,283	19,456	17,283	17,283	19,421	19,421
RSF with CANESM2 GCM[a]	0.204	15,259	15,259	15,699	15,259	15,259	15,629	15,629
RSF with IPSL-CM5A-MR GCM[b]	0.204	13,734	13,734	14,072	13,734	13,734	14,054	14,054
RSF with CCSM4 GCM[c]	0.204	14,713	14,713	15,121	14,713	14,713	15,035	15,035
Expected value		15,624	15,624	16,711	15,624	15,624	16,662	16,662

[a]A second-generation Canadian Earth System GCM.

[b]An Institut Pierre Simon Laplace GCM.

[c]A Community Climate System GCM.

TABLE 4 Predicted numbers of mountain goat populations that will meet trend objectives in 1 generation (9 yr) in Montana, USA. We defined increasing as a population predicted to be ≥20% higher than in 2020 (representing mean annual population growth of 2%), decreasing as a population predicted to be ≥20% lower than in 2020 (representing mean annual population decline of 2%), and stable as a population predicted to be <20% higher or lower than in 2020. Model weights represent an approximately normal distribution of predictions for each population. Expected values are weighted means (using the model weights) of the distribution of population simulation model predictions. Alternative strategies focused on population monitoring and conservative harvest management (status quo), restricting mortality from harvest and predation from carnivores (top-down mortality management), translocating mountain goats into currently unoccupied areas (introduction), augmenting small, struggling, or declining populations (augmentation), protecting seasonal habitats from human use (habitat protection), and combined actions from above strategies with or without augmentations (combined with augmentations and combined, no augmentations).

Model	Model weight	Status quo	Mortality management	Introduction	Augmentation	Habitat protection	Combined with augmentations	Combined, no augmentations
Lower 0.025 of simulated values	0.025	2	2	7	6	2	6	5
Lower 0.25 of simulated values	0.25	9	11	13	19	11	19	12
Median simulated value	0.45	15	17	20	26	15	26	17
Upper 0.75 of simulated values	0.25	26	35	28	36	27	36	32
Upper 0.975 of simulated values	0.025	46	53	50	48	47	55	54
Expected value		16.7	20.5	20.7	26.8	17.5	27.0	20.1

TABLE 5 Predicted number of bighorn sheep and mountain goat populations with pneumonia-associated pathogens in Montana, USA, following implementation of management beginning in 2020 under 3 alternative hypotheses (top half of table) and risk value functions accounting for risk tolerance for mixing populations during translocations. Lower values of the risk value function indicate less risk. We calculated the risk value function using the mean microbial mixing risk multiplier (*M*) of 1.6, minimum (0) and maximum (3) values. We elicited *M* and model weights from wildlife biologists responsible for mountain goat management, wildlife health program staff from Montana Fish, Wildlife & Parks, and academic collaborators with expertise in disease ecology and veterinary science. Expected values are weighted means (using the model weights) of individual model predictions for each species. Alternative strategies focused on population monitoring and conservative harvest management (status quo), restricting mortality from harvest and predation from carnivores (top-down mortality management), translocating mountain goats into currently unoccupied areas (introduction), augmenting small, struggling, or declining populations (augmentation), protecting seasonal habitats from human use (habitat protection), and combined actions from above strategies with or without augmentations (combined with augmentations and combined, no augmentations).

Model for pneumonia pathogens and model weight (w)	Species[a]	Status quo	Mortality management	Introduction	Augmentation	Habitat protection	Combined with augmentations	Combined, no augmentations
Only populations currently known to have pneumonia pathogens harbor them (w = 0.04)	BHS	1	1	2	5	1	7	2
	MG	24	24	26	29	24	30	26
All populations harbor these pathogens (w = 0.50)	BHS	29	29	31	29	29	31	31
	MG	58	58	63	58	58	61	61
Populations with historical range overlap with domestic sheep have these pathogens (w = 0.46)	BHS	29	29	31	29	29	31	31
	MG	56	56	60	56	56	59	59
Expected value	BHS	27.8	27.8	29.8	28.0	27.8	30.0	29.8
	MG	55.7	55.7	60.1	55.9	55.7	58.8	58.6
Number of populations being mixed	BHS	0	0	2	8	0	8	2
	MG	0	0	2	10	0	13	3

(Continues)

TABLE 5 (Continued)

Model for pneumonia pathogens and model weight (*w*)	Species[a]	Status quo	Mortality management	Introduction	Augmentation	Habitat protection	Combined with augmentations	Combined, no augmentations
Model-weighted risk value function, $M = 0$	BHS	27.8	27.8	29.8	28.0	27.8	30.0	29.8
	MG	55.7	55.7	60.1	55.9	55.7	58.8	58.6
Model-weighted risk value function, $M = 1.6$	BHS	27.8	27.8	33.0	40.7	27.8	42.7	33.0
	MG	55.7	55.7	63.3	71.8	55.7	79.5	63.4
Model-weighted risk value function, $M = 3$	BHS	27.8	27.8	35.8	52.0	27.8	54.0	35.8
	MG	55.7	55.7	66.1	85.9	55.7	97.8	67.6

[a]MG = mountain goat; BHS = bighorn sheep.

climate change effects, mountain goats could occupy as much as 5,300 km^2 more area under the model assuming climate change will not impact the distribution of mountain goat populations. The EVPI equaled 0 for resolving uncertainty in predicted area of future suitable habitat because AMS involving introductions would result in more occupied suitable habitat under every model considered (Table 3).

Uncertainty about mountain goat population demography and dynamics had a large effect on the number of mountain goat populations predicted to meet trend objectives in 1 generation (Table 4), with predictions ranging from 2 (3%) to 55 (95%) populations. The EVPI was >0 for resolving uncertainty in numbers of populations that will meet trend objectives in 1 generation. Accordingly, the optimal choice among AMS is affected by uncertainty in mountain goat demography and population dynamics.

Uncertainty about pneumonia pathogens and risk of mixing pathogens during translocations had a large effect on the bighorn sheep and mountain goat risk value functions (Table 5). We predicted that 3–100% of bighorn sheep populations sympatric with mountain goats, and 41–100% of current mountain goat populations, would be exposed to pathogens from sympatric mountain goats or bighorn sheep under the models and AMS we considered (Table 5). The EVPI equaled 0 because AMS without translocations resulted in fewer exposed mountain goat and bighorn sheep populations under every model (Table 5). When considering only AMS with translocations, EVPI was >0, indicating that if translocations are to be implemented, resolving uncertainty about which populations harbor pneumonia-associated pathogens would affect which AMS is optimal.

DISCUSSION

We used a decision analytic framework to determine predicted efficacy of alternative strategies for mountain goat management in Montana. Predicted outcomes accounted for uncertainty in effects of climate change, demographics and population dynamics, and respiratory disease risks to bighorn sheep and mountain goats, at a large spatial scale. We elicited and analyzed individual differences in values and risk tolerance from wildlife biologists responsible for mountain goat population and habitat management. This enabled us to identify recommendations and priority information needs for mountain goat management across Montana. Our approach serves as a case study for decision analysis of optimal wildlife and habitat management strategies under climate change. Couching our analyses within a decision analysis context allowed us to incorporate the uncertain, indirect effects of climate change on an alpine species while also predicting and considering other biological uncertainties and multiple objectives. This approach is applicable to many terrestrial species and systems where climate change may have an impact, when other concerns and tradeoffs are involved.

Our decision analysis revealed that establishing new mountain goat populations is a climate change resilient strategy (Peterson et al. 2003). We predicted that successful introductions would increase the area of suitable habitat occupied by mountain goats at mid-century, regardless of climate change effects on habitat distribution. Our decision framework included translocations to previously occupied native ranges and new areas. Past efforts to establish new populations in Montana have successfully increased the total area presently occupied (DeCesare and Smith 2018). The habitat and climate models we used to forecast mountain goat habitat produced variable predictions of area that would be occupied at mid-century. New introductions could be strategically conducted to determine relative accuracy of model predictions, but area occupied at mid-century may be reduced if some introductions fail because habitat is reduced by climate change. Given relatively few population introductions might realistically be conducted before mid-century, a more productive approach might be to conduct population introductions into areas where RSF model predictions and GCM forecasts align to represent high-quality habitat (equal-area bins 9 and 10 in our RSF models) at mid-century.

Mountain goat translocations could increase exposure to pneumonia-associated pathogens and mix microbial communities among mountain goats and bighorn sheep. Translocations have a long history in mountain goat management, and individual perceptions of risk posed from mixing microbial communities (represented by M)

affected the optimality of augmentations or population introductions. Risk aversion reduced the support for strategies with augmentations. Risk stems from uncertainty in outcomes, but risk tolerance is an individual attribute that varies among people, situations, and perspectives (Keeney 1992, Runge and Converse 2020). Rather than a single, statewide value of *M*, allowing *M* to vary among local situations may have revealed location-specific variation in risk tolerance and support for translocations.

The wide variation in risk attitudes within a small working group composed of wildlife professionals suggests that wide variation in risk attitudes likely also exists among elected and appointed decision makers, other agency staff, the public, and stakeholders such as alpine ungulate advocates and domestic sheep producers. Information about tolerances among these groups for taking pathogen-related risks during translocations would help decision makers choose appropriate actions. This could also help increase transparency about risks and the rationale for taking those risks. Information about whether attributes of individual populations affect risk tolerance (e.g., current abundance or pathogen exposure) may also help incorporate risk into decision-making. Such information could help guide the fundamental choice between a risk-averse strategy without translocations and a risk-tolerant strategy involving translocations. This choice could be made at a statewide level prior to considering management actions to implement in specific locations or could emerge from an amalgamation of local support for or aversion to taking risks in specific areas and populations. Knowledge gain could potentially be maximized by considering large spatial and temporal scales (e.g., by providing opportunities for translocations to succeed or fail because of disease epidemics over several trials). At the local scale, however, given high public interest in specific mountain goat and bighorn sheep populations, the perspective in the decision framework will differ, and persistence and effects on specific populations of interest will be a primary consideration (Sells et al. 2016).

Our EVPI analyses identified 2 priority information needs for mountain goats in Montana. First is a need to decrease uncertainty about mountain goat population dynamics, including estimates of mountain goat population sizes, vital rates, and age structures and inferences regarding effects of carnivore harvest, habitat protection, and translocations on mountain goat survival and fecundity. Our population model assumed a stable-age distribution, that vital rates are consistent with those recorded in Alberta and Alaska (Hamel et al. 2006, Côté and Hamel 2018, White et al. 2018), and that mean values and variance of survival and fecundity will be improved by increasing carnivore harvest, protecting seasonal ranges from human use, and augmenting mountain goat populations. These last assumptions lead to predictions of positive effects of taking these actions, yet no empirical data exist to support these assumptions.

Analyses are also needed to determine the viability of struggling populations. Our predictions for area of suitable habitat occupied by mountain goats did not account for loss of occupied area resulting from future extirpations that may occur. To do this would have required a habitat-linked population model to project population dynamics decades into the future, which we did not think was advisable because of the additional information and assumptions required for this data-poor species. We therefore separated habitat and population modeling, which induced the assumption that struggling populations will not be extirpated by mid-century. This assumption likely results in positive bias in predictions for strategies that do not attempt to improve trends in struggling populations. We also assumed the 58 extant populations are not composed of smaller, disconnected herds. Violation of this assumption would increase extirpation probabilities in those smaller herds (White et al. 2021). High probabilities of extirpation would likely increase tolerance of decision makers for taking risks, such as those that occur with population augmentations.

The second priority information need centers on pneumonia pathogens. If translocations are implemented in the future, more information is needed on pneumonia-associated pathogens and effects of mixing pathogen communities in mountain goat and bighorn sheep populations during translocations. Sampling pathogen communities will not always clarify translocation decisions because of limited sample sizes and imperfect detection (Butler et al. 2017), combined with incomplete knowledge about the etiology of pneumonia epidemics (Cassirer et al. 2018), but pathogen sampling will allow more precise enumeration of risks and facilitate learning about the consequences of mixing specific pathogens during translocations. Empirical data on effects of mixing microbial communities would help establish a biological rationale for values used for M, with implications for management strategies involving translocation.

Our EVPI analysis results suggest that information needs related to population dynamics and disease risks will affect optimal choices of management strategies and actions to achieve fundamental objectives. Because management actions are likely to be repeated in time and space, these uncertainties could be reduced in an adaptive management program (Conroy and Peterson 2013). Focused research and monitoring programs could be implemented in concert with management actions to decrease uncertainties and improve future achievement of objectives. These information needs are closely related. Population dynamics data will be key to understanding effects of pneumonia pathogens and management actions that affect disease risks (Cassirer et al. 2013, Butler et al. 2018). Accordingly, integrated models of effects of management actions, pathogen mixing, and other drivers of vital rates could be used in combination with targeted research and monitoring to facilitate learning and improve future decisions (Arnold et al. 2018). These models could be developed to rigorously evaluate alternative hypotheses of the drivers of population dynamics and disease risks, including the effects of management actions, thereby reducing uncertainty and improving predictive accuracy over time. The design of an adaptive management program must also account for risk tolerance for pneumonia epidemics. Risk aversion will make management options without translocations preferred, eliminating the need to reduce uncertainty about how translocations affect pneumonia epidemic risks. Risk-neutral or risk-seeking attitudes will make management options with translocations preferred, necessitating efforts to reduce uncertainty about how translocations affect pneumonia epidemic risks. More information about population dynamics and effects of management actions other than translocations would improve future decisions regardless of disease risk tolerance.

MANAGEMENT IMPLICATIONS

The distribution of mountain goat and bighorn sheep populations overlap substantially, they share similar niches and pathogens, and management objectives for each species are similar and marked by the need to consider local risk tolerance for pneumonia epidemics. We recommend that wildlife managers develop an integrated adaptive management program for these species. Wildlife managers can work with stakeholders to decide on a risk-averse or risk-tolerant strategy to incorporating translocations into local herd management, either at a large scale or by compiling tolerances for taking risks in specific populations. Translocations to establish new populations are a climate-resilient strategy that we predict will increase the distribution of mountain goat populations, and augmentations may have a large effect on the number of populations meeting trend objectives; however, these actions will induce disease risks that may not be tolerable. Once this risk-tolerance course is set, wildlife managers can define an adaptive management program that outlines specific management actions in specific populations paired with targeted research and monitoring that will reduce key uncertainties to improve future outcomes. The choice of management actions in specific populations to include in this program should be guided by efficiency in reduction of key uncertainties to improve future management actions, community support and risk tolerance in the populations where the management actions will be taken, and logistical and financial realities.

ACKNOWLEDGMENTS

We appreciate the tireless work and focus on this project by the working group members from FWP, the United States Forest Service, the National Park Service, the North Central Climate Adaptation Science Center, Montana State University, and University of Montana. We also appreciate their efforts to collect and maintain the data and information that we relied on during this project. Additionally, we thank S. A. Courville (deceased) and C. D. Becker (retired) from the Confederated Salish and Kootenai Tribal Wildlife Program for providing data and insights throughout the working group process. We thank FWP Wildlife Health Program staff for participating in the elicitation of values for the microbial mixing risk multiplier. We are very grateful to S. D. Côté and M. S. Russell for sharing updated vital rate information from mountain goat studies in Alberta. K. S. White, M. A. Hurley, B. L. Smith, and K. G. Smith provided invaluable insights during this project. Two anonymous reviewers and S. D. Côté provided reviews that greatly improved this manuscript. Funding to conduct this work and the associated workshops was provided by the sale of hunting and fishing licenses in Montana, annual Federal Aid in Wildlife Restoration grants to Montana Fish, Wildlife & Parks, the United States Forest Service, the National Park Service, and the North Central Climate Adaptation Science Center.

CONFLICTS OF INTEREST

The authors declare no conflicts of interest.

ETHICS STATEMENT

No live animals were handled or harmed as part of this research.

DATA AVAILABILITY STATEMENT

The data used for this study are available publicly by contacting Montana Fish, Wildlife and Parks.

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Associate Editor: Steeve Côté.

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How to cite this article: Gude, J. A., N. J. DeCesare, K. M. Proffitt, S. N. Sells, R. A. Garrott, I. Rangwala, M. Biel, J. Coltrane, J. Cunningham, T. Fletcher, K. Loveless, R. Mowry, M. O'Reilly, R. Rauscher, and M. Thompson. 2022. Demographic uncertainty and disease risk influence climate-informed management of an alpine species. Journal of Wildlife Management 86:e22300. https://doi.org/10.1002/jwmg.22300