The Journal of Wildlife Management 75(5):1121–1127; 2011; DOI: 10.1002/jwmg.153

Research Article

Predicting Spatial Distribution of Human–Black Bear Interactions in Urban Areas

JEROD A. MERKLE,[1] *Boone and Crockett Program in Wildlife Conservation, Wildlife Biology Program, University of Montana, Missoula, MT 59812, USA*

PAUL R. KRAUSMAN, *Boone and Crockett Program in Wildlife Conservation, Wildlife Biology Program, University of Montana, Missoula, MT 59812, USA*

NICHOLAS J. DECESARE, *Wildlife Biology Program, University of Montana, Missoula, MT 59812, USA*

JAMES J. JONKEL, *Montana Fish, Wildlife and Parks, 3201 Spurgin Road, Missoula, MT 59804, USA*

ABSTRACT Human–wildlife interactions are often associated with a myriad of stakeholder groups, intense political scrutiny, and limited biological data, creating complex decision-making situations for wildlife management agencies. Limited research exists on the development and testing of tools (e.g., models to predict the spatial distribution of interactions) to reduce human–black bear (*Ursus americanus*) interactions (HBI). Available models predicting spatial distribution of HBI are usually developed at scales too large to predict across urban areas, are rarely tested against independent data sets, and usually do not incorporate both landscape and anthropogenic variables. Our objective was to develop a predictive modeling tool that could identify areas of high conflict potential across urban landscapes. We compared locations of HBI in Missoula, MT, recorded by Montana Fish, Wildlife & Parks from 2003 to 2008, to random locations using logistic regression. The final model discriminated the relative spatial probability of HBI within Missoula well, and a second study area moderately. The probability of HBI in Missoula increased when residents lived close to forested patches and major rivers and streams and in intermediate housing densities (approx. 6.59 houses/ha). Our results provide a wildlife management tool and a repeatable statistical framework that predicts spatial distribution of HBI using only a small set of variables.

KEY WORDS black bear, conflicts, distribution modeling, human–bear interactions, Montana, *Ursus americanus*.

Although research investigating human–wildlife interactions is available (Conover 2002), managers dealing with human–black bear (*Ursus americanus*) interactions (HBI) still develop management plans without rigorous development and testing of certain management practices (Beckmann et al. 2004, Ferraro and Pattanayak 2006, Gore et al. 2008). For example, the authors from only one study systematically developed an education effort to reduce the number of HBI and tested its efficacy on changing human behavior (Gore et al. 2008). Education efforts have few short-term effects on human behavior, and integrating evaluation measures is essential to implementing education efforts (Gore et al. 2008). These results, along with the increasing trend in HBI over the last few decades in North America (Beckmann and Berger 2003, Zack et al. 2003, Baruch-Mordo et al. 2008), exemplify the need to develop and test best management practices to reduce HBI.

To successfully reduce the number of HBI, managers should have a suite of tools that allow them to spatially identify developed areas and areas scheduled for development with high probability of conflict (Sitati et al. 2003, Wilson et al. 2006, Kretser et al. 2008). The ability to predict interactions across urban areas is essential to successfully identify where to implement proactive management efforts and plan urban development that minimizes HBI. Researchers have recently demonstrated the value of spatial modeling to investigate the distribution of human–wildlife interactions for species other than black bears (Sitati et al. 2003, Bradley and Pletscher 2005, Michalski et al. 2006). Similarly, prediction models in rural areas and at statewide scales have been developed for black and grizzly (*U. arctos*) bears using locations of bear sightings, incidents, and reactive management actions collected by state management agencies (Wilson et al. 2006, Ambarli and Bilgin 2008, Baruch-Mordo et al. 2008, Kretser et al. 2008). No studies however, have tested the validity of their models using independent data sets in adjacent study areas (Verbyla and Litvaitis 1989), which would be beneficial for managers to predict human–wildlife interactions in areas considered for development.

A clear pattern exists regarding the spatial predictive variables used in studies predicting HBI and other human–wildlife interactions. Variables used in all studies are explicably linked to 2 distinctive categories: landscape variables

Received: 12 August 2010; Accepted: 16 November 2010;
Published: 1 June 2011

[1]*E-mail: jerod.merkle.1@ulaval.ca*

(e.g., distance to habitat feature) and anthropogenic variables (e.g., housing density, grazing regime). However, few research studies include both landscape and anthropogenic variables within the same predictive model (Wilson et al. 2006). Important variables to predict HBI include distance to black bear habitat (Baruch-Mordo et al. 2008), distance to riparian areas (Wilson et al. 2006), and housing density (Kretser et al. 2008). No studies have incorporated all 3 suggested variables into one model to predict spatial distribution of HBI and developed prediction models across urban areas where most HBI occur (Spencer et al. 2007).

Our objective was to provide wildlife managers with a tool that is broadly applicable, practical, and repeatable and would allow them to predict the spatial arrangement of future HBI across urban areas. In developing the tool, we tested the predictive ability of 3 variables used in other HBI studies. We expected a negative relationship between probability of HBI and distance to forest patches, distance to major rivers and streams, and housing density (Kleckner 2001, Wilson et al. 2006, Baruch-Mordo et al. 2008).

STUDY AREA

Missoula, MT (61.9 km^2) was inhabited by approximately 64,801 people. There were 25,225 housing units at a mean density of 4.08/ha, with 10.46 people/ha (U.S. Census Bureau 2000). Missoula was situated in a valley bottom, where the Clark Fork and Bitterroot rivers converge. Landownership in surrounding parcels was a mix of private and public (i.e., United States Department of Agriculture [USDA] Forest Service) lands. Topography was diverse with elevations ranging from 978 m to 2,766 m. Most urban development was on the valley floor, and steep slopes and canyons characterized the surrounding mountains (Fig. 1).

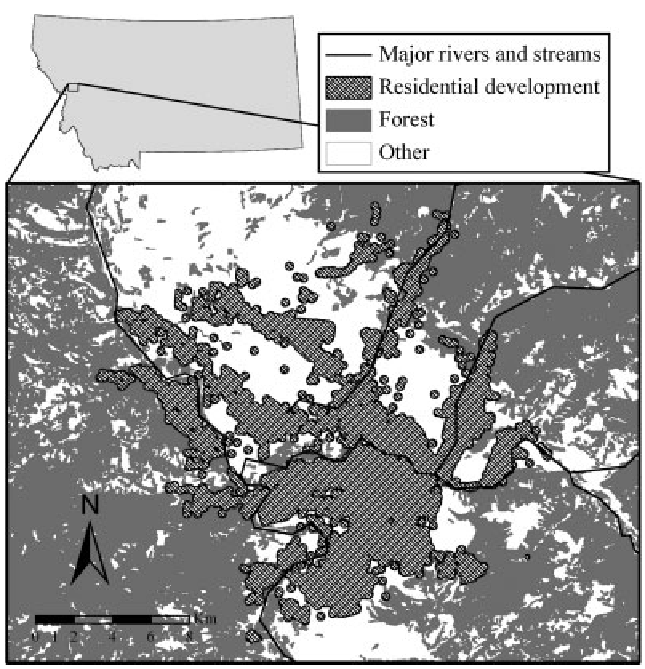

Figure 1. Spatial distribution of urban development, major rivers and streams, and forested areas where human–black bear interactions occur in and around Missoula, Montana, USA. Areas in white include agricultural and industrial lands and grassland and shrub dominated vegetation.

Average annual precipitation was 43.3 cm evenly distributed throughout the seasons except for May and June when rain was more common (Western Regional Climate Center 2008).

Seeley Lake, MT (28.6 km^2) was 50 km northeast of Missoula and was inhabited by approximately 1,436 people. There were 938 occupied housing units at a mean density of 0.33/ha, with 0.50 people/ha (U.S. Census Bureau 2000). The town was situated in the Clearwater River Valley at 1,228 m in elevation. Spatial dynamics of urban development in Seeley Lake were similar to Missoula, with a concentrated central area and multiple radiating protrusions of housing development. Landownership in surrounding parcels was a mix of private and public (i.e., USDA Forest Service) lands. Average annual precipitation was 50.8 cm evenly distributed throughout the seasons except December, January, May, and June when precipitation was more frequent (Western Regional Climate Center 2008).

In both study areas, rain ordinarily fell April–October and snow fell from November–March. Human–black bear interactions occurred in both study areas, and Montana Fish, Wildlife & Parks (MFWP) was responsible for managing these interactions. Attractants related to HBI in both areas included garbage, fruit trees, bird seed, composts, chickens, and barbeque grills (Booth 2005).

METHODS

From 2003 to 2008, MFWP systematically recorded HBI in 2 databases. The first database included phone calls concerning human–black bear incidents and sightings unrelated to black bear hunter harvest. Information from each phone call included date, address, nature of interaction (e.g., sighting only, bear getting into trash, bear getting into bird feeders), attractant related to interaction, and physical appearance of the bear. The second database included all reactive management actions carried out by MFWP personnel. Reactive management actions occurred when MFWP personnel responded to an individual bear through immediate and direct action, using methods such as capture, aversive conditioning, translocation, or removal of individuals from the population (Hopkins et al. 2010). Information for each reactive management action included date, mailing address where interaction took place, nature of interaction, attractant related to interaction, and action taken (e.g., aversive conditioning, set trap). We combined these 2 databases into a pooled spatial data set of HBI and categorized records into sighting only, other interaction (i.e., HBI that are not sightings or reactive management actions), and reactive management action. We omitted all records that did not explicitly fall into these categories.

We used Google Earth Free (Google, Mountain View, CA) as geocoding software to obtain Universal Transverse Mercator (UTM) coordinates from the mailing address of each record. To improve geocoding data, we adjusted coordinates given by Google Earth to consistently mark the centroid of the dwelling's roof centerline (Goldberg et al. 2008). We also used 2 other methods to minimize error in location approximation. First, when we obtained a geocoded location in the middle of a street, we used the convention of odd–even addresses being associated with north–south and east–west properties, respectively, to obtain more precise UTM coordinates. Second, we contacted the MFWP manager who recorded the phone call or reactive management action to verify questionable locations. We omitted coordinates given by Google Earth that were ambiguous or incomprehensible, not associated with a property, or not recalled by the manager. We assumed a negligible effect on sampling bias by omitting locations, because the omitted locations constituted <6% of all locations.

Modeling

We used 6 years (2003–2008) of HBI data and compared locations of HBI to 5,000 locations randomly selected across Missoula using a use-available sampling framework (Manly et al. 2002). The available extent for selecting random locations included all areas within 100 m (roughly the width of an average city block within the study area) of an occupied dwelling or business parcel where HBI could occur. We buffered center locations of parcels with residential dwellings and businesses (Montana Natural Resources Information System 2009) by 100 m and drew random locations within this buffered zone of availability. We omitted privately owned parcels classified as vacant and agricultural to limit our inferences within occupied urban areas.

We developed models using logistic regression to discriminate between HBI and random locations, analogous to resource selection function techniques (Hosmer and Lemeshow 2000, Manly et al. 2002). We used multi-variable models to derive a relative probability of a human–black bear interaction using the formula:

$$\hat{\omega}(x) = \exp(\hat{\beta}_1 x_1 + \hat{\beta}_2 x_2 + \cdots + \hat{\beta}_n x_n) \qquad (1)$$

where $\hat{\omega}(x)$ is the relative probability of a sighting or incident (i.e., low to high) as a function of an array of covariates x_n, and variable coefficients $\hat{\beta}_n$ (Hosmer and Lemeshow 2000, Manly et al. 2002, Keating and Cherry 2004, Johnson et al. 2006). In developing our models, we assumed that 1) HBI reported by the public reflect the actual distribution of all HBI that occur within our study area (reported or not reported); 2) there were no biases in data collection, recording, or geocoding; 3) each HBI location was an independent event; and 4) errors in the location of HBI were normally distributed.

Spatial Explanatory Variables

We selected potential spatial explanatory variables based on 2 conditions. First, variables must have been publicly available, easy, and inexpensive to obtain (Sitati et al. 2003), so our modeling framework could be replicated by managers and researchers in other areas. Second, variables must have been supported by previous literature and biological relevance. The variables we considered stemmed from a combination of landscape and anthropogenic factors and included distance to major rivers and streams (i.e., riparian vegetation; Wilson et al. 2006), housing density (Kleckner 2001, Kretser et al. 2008), and distance to forest patches (i.e., suitable bear habitat; Baruch-Mordo et al. 2008). We divided forest patches into 2 categories based on land use planning (Soulé 1991) and foraging theory (Pyke et al. 1977). We assumed that the relationship between the locations of HBI and forested areas large enough to sustain a bear home range (meeting all life history requirements for black bears, similar to core habitats; Larkin et al. 2004) and small forest patches used intermittently throughout the year (similar to high human disturbance land cover types; Larkin et al. 2004) would be different.

We used TIGER 2000 Census data (U.S. Census Bureau 2009) to delineate water bodies for measuring distance to major rivers and streams (i.e., riparian vegetation). We omitted artificial waters, man-made ditches, and diversion canals from the database, and we calculated the distance to major rivers and streams (km) for each location using ArcGIS 9.2 (Environmental Systems Research Institute, Redlands, CA).

We estimated spatial housing density from parcel information accessed from the Montana Cadastral Mapping Project (Montana Natural Resources Information System 2009). We estimated a centroid location within each parcel containing an occupied residential dwelling or business, omitting privately owned parcels classified as public, vacant, or undeveloped. We then used the density function in ArcGIS 9.2 to create a housing density (houses/ha) raster.

To delineate forested areas we used landcover data from the Vegetation Mapping Project (VMAP) geospatial database (USDA Forest Service 2006). We merged all vegetation classes dominated by a forest-related tree species and with ≥25% canopy cover to develop one forest layer. We then calculated the area of each contiguous forest patch and characterized patches as large (>100 km^2; based on 95% fixed kernel estimator [Worton 1989] of a male bear collared in the study area; J. A. Merkle and P. R. Krausman, University of Montana, unpublished data) or small (≤100 km^2). We calculated distance to each large and small forest patch for each location using ArcGIS 9.2.

Analysis

We developed multi-variable logistic regression models that included distance to large and small forest patches, distance to major rivers and streams, housing density, and interactions between housing density and all other variables. The response variable was whether or not an interaction occurred at the specified location. We screened all variables for colinearity (based on a cutoff threshold value of $r = 0.5$) and used univariate logistic regression to identify candidate variables ($P < 0.25$) for inclusion in multi-variable modeling (Hosmer and Lemeshow 2000). We used forward stepping model selection with likelihood ratio tests to assess variable significance and considered additional polynomial and interaction terms (Hosmer and Lemeshow 2000). This approach resulted in a one final model, which was the most parsimonious model including only predictive explanatory variables. We used Stata 10 (StataCorp, College Station, TX) for all analyses.

We tested the validity of our model first by generating predictions used to create the final model from where the data were collected (i.e., Missoula) and second by applying the final model predictions across Seeley Lake for a more unbiased validation of the final model (Verbyla and Litvaitis 1989). We used *K*-folds cross validation to partition the data into model training and model testing datasets, based on 5 random divisions ($k = 5$) of 80% and 20% training and testing data, respectively (Huberty 1994, Boyce et al. 2002). We assessed predictive power of the final model by comparing 5-fold training model predictions to observed distributions of withheld locations (Boyce et al. 2002). We partitioned predicted values from testing data into 10 equal-area ranked bins representing low to high training data predictions. We then used Spearman rank correlations (r_s) to compare the number of withheld locations within each standardized bin to the respective bin ranking (Boyce et al. 2002).

We subsequently obtained locations of HBI ($n = 79$) collected between 2003 and 2008 in Seeley Lake, MT. Although sightings were not included in this sample (i.e., sightings were not recorded in Seeley Lake), the database was similar to Missoula's because information was collected by the same regional office within MFWP. Using coefficients from the final model developed in Missoula, we predicted the relative spatial probability of HBI in Seeley Lake based on the same spatial variables used in Missoula. We then tested the predictive power of the model by comparing Missoula training model predictions to Seeley Lake testing locations. We used Spearman rank correlations (r_s) to compare the number of HBI from Seeley Lake that fell within 10 standardized ranked bins produced from the Missoula training model predictions (Boyce et al. 2002).

RESULTS

We geocoded 917 HBI in Missoula, MT (284 sightings, 103 reactive management actions, 530 other incidents) from 2003 to 2008 ($n = 132$, 257, 150, 160, 105, 113, respectively). Most other incidents and reactive management actions (72%) involved anthropogenic attractants, such as garbage ($n = 284$), fruit trees ($n = 72$), bird feeders ($n = 52$), freezers ($n = 16$), livestock grain ($n = 6$), barbeque grills ($n = 6$), chickens ($n = 6$), pet food ($n = 6$), and compost piles ($n = 5$).

Landscape and anthropogenic variables, including distance to large forest patches, housing density, distance to major rivers and streams, and an interaction between housing density and distance to large forest patches, had predictive power in the final model (Table 1). Correlations among variables ranged from $r = 0.045$ to $r = 0.495$. Distance to major rivers and streams and housing density were nonlinear predictors so we included quadratic relationships (i.e., squared terms) in the model for these variables. Distance to small forest patches was a significant univariate predictor ($Z = -11.67$, $P < 0.001$) but did not contribute significantly to the final multivariate model. The final model described the spatial distribution of interactions ($\chi^2_6 = 1105.08$, $P < 0.001$), and probability of a HBI was negatively associated with distance to large forested patches and distance to major rivers and streams and was positively associated with intermediate housing densities (approx. 6.59 houses/ha; Table 1) in Missoula. Spatial predictions from the final model portrayed patterns of high probability of HBI in all valleys protruding from the city core and in housing developments associated with the western wildland–urban interface of Missoula (Fig. 2).

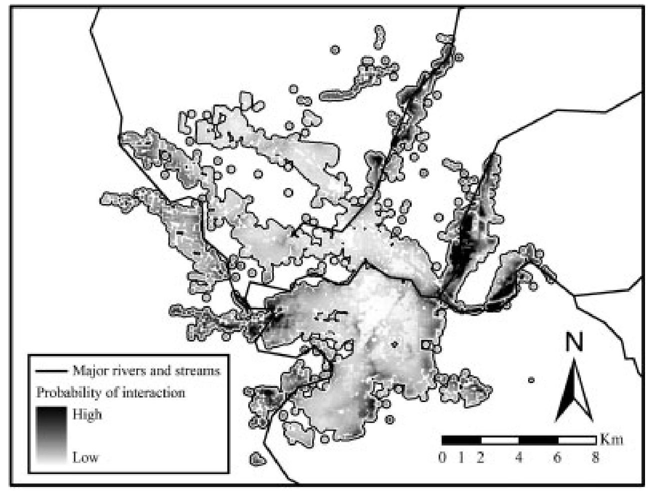

Figure 2. Distribution of human–black bear interaction probabilities across urban development in Missoula, Montana, USA. Probabilities estimated using a final logistic regression model with distance to major rivers and streams, distance to forest patches, and housing density as variables. Model developed from human–black bear interaction locations collected between 2003 and 2008 in Missoula.

Spearman rank correlations between the frequency of HBI and the 10 standardized bins suggested good models for the *K*-folds cross validation ($r_s = 0.88$, SE $= 0.03$, $P < 0.01$; Fig. 3). We also successfully applied the final model developed in Missoula to Seeley Lake (Fig. 4), and the model predicted the locations of HBI recorded in study area 2 moderately ($r_s = 0.65$, $P = 0.041$; Fig. 3). All model testing

Table 1. Parameter estimates for a final logistic regression model based on locations of human–black bear interactions collected between 2003 and 2008 in Missoula, MT, USA. The model includes anthropogenic and landscape variables and estimates the relative probability of human–black bear interactions.

				95% CI for coefficient	
Variable	**Coefficient**	**SE**	***P***	**Lower**	**Upper**
Distance to large forest patches (km)	−0.496	0.054	<0.001	−0.602	−0.390
Housing density (houses/ha)	0.553	0.047	<0.001	0.462	0.645
Housing density^2 (houses/ha)	−0.022	0.005	<0.001	−0.031	−0.012
Distance to water bodies (km)	−2.074	0.298	<0.001	−2.659	−1.490
Distance to water bodies^2 (km)	0.766	0.194	<0.001	0.384	1.147
Housing density × distance to forest	−0.140	0.018	<0.001	−0.175	−0.104
Constant	−0.969	0.092	<0.001	−1.150	−0.788

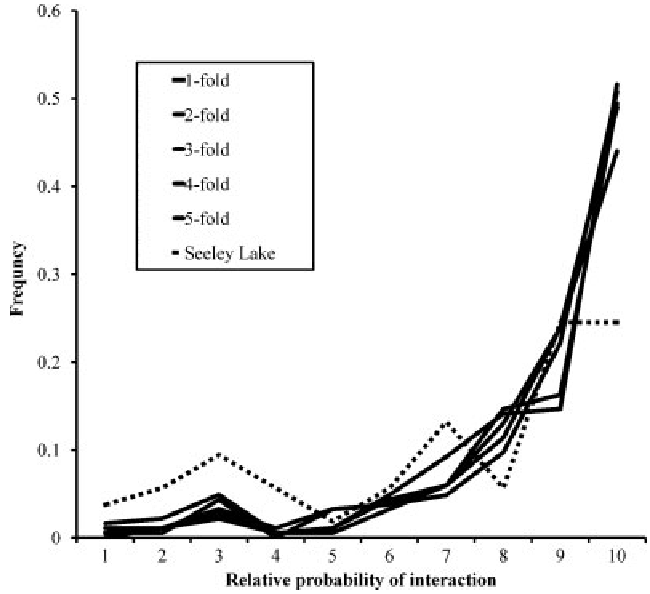

Figure 3. Frequency of actual human–black bear interaction locations across 10 equal-area (i.e., percentile classification) ranked bins of predicted relative probability of interaction scores for *K*-folds cross validation and an external (human–black bear incidents in Seeley Lake, Montana) independent data set. Final logistic regression model was developed, using distance to major rivers and streams, distance to forest patches, and housing density as variables, from human–black bear interaction locations collected between 2003 and 2008 in Missoula, Montana.

procedures supported the final model, where residents who lived close to major rivers and streams, close to large forest patches, and in intermediate housing densities were at a higher risk of HBI.

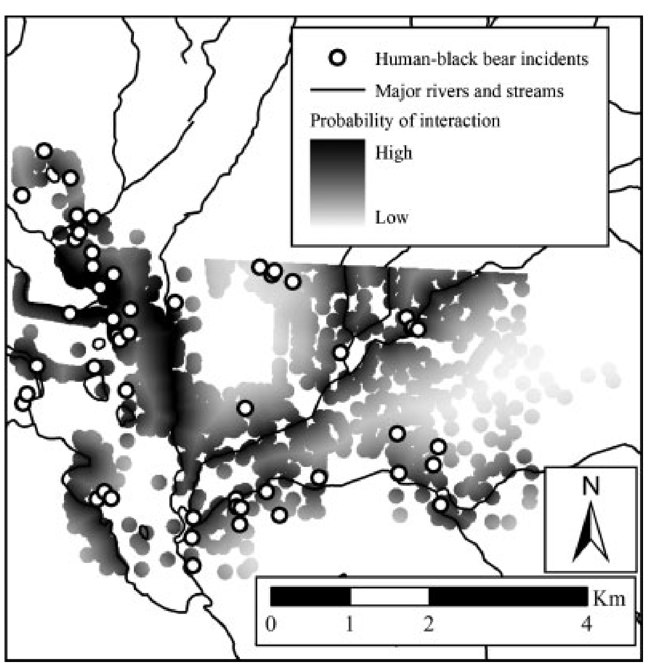

Figure 4. Location of actual human–black bear incidents (i.e., other interactions and reactive management actions) recorded from 2003 to 2008 in Seeley Lake, Montana, USA, and distribution of predicted human–black bear interaction probabilities based on a final logistic regression model of human–black bear interaction locations collected between 2003 and 2008 in Missoula, Montana.

DISCUSSION

Urban expansion into natural landscapes has affected biotic integrity, species composition, and wildlife behavior (Kretser et al. 2008), resulting in increasing trends in the number of reported human–wildlife interactions (Conover 2002). Managers responsible for reducing HBI need an array of information (from public education programs to best aversive conditioning practices) to be successful in dealing with this complex issue. The ability to predict spatial distribution of HBI will focus proactive management by allowing for efficient identification of areas with high and low conflict potential. Our results provide a wildlife management tool and a repeatable statistical framework, which predicts the spatial distribution of HBI using only a small set of variables.

In accordance with our expectations, we found a negative relationship between probability of HBI and distance to large forest patches (linear relationship) and distance to major rivers and streams (nonlinear relationship). However, probability of HBI was not negatively associated with housing density, but negatively quadratic in form, where higher probabilities of HBI were positively associated with intermediate housing densities in Missoula. Results from our model selection procedure also suggested an interaction between housing density and distance to large forest patches (Table 1), meaning that residents living in intermediate housing densities (with respect to our study area) that are located near large forested areas have the highest risk of HBI. Our final model developed in Missoula was moderately effective in identifying the locations of HBI in Seeley Lake, MT (Fig. 4), suggesting that these variables and this type of modeling procedure can be used across study areas. Specific variable coefficients however, may need to be refined because of the diversity of housing densities in western Montana and other urban areas in North America.

Although scale is an important consideration when developing habitat-related models (Wiens 1989), we found similar predictive variables to studies examining HBI at larger scales (i.e., across states or rural areas; Wilson et al. 2006, Baruch-Mordo et al. 2008, Kretser et al. 2008), which is not surprising considering the parallels between the variables used in our model and variables known to be important predictors of black bear habitat use. Forested areas and riparian zones are vegetation associations used by black bears across their range (Jonkel and Cowan 1971, Young and Beecham 1986, Fecske et al. 2002, Brodeur et al. 2008), and housing density may be a surrogate for factors that affect mortality (e.g., road kill; Fecske et al. 2002, Baruch-Mordo et al. 2008), anthropogenic resources (e.g., abundance of garbage; Badyaev 1998, Beckmann and Berger 2003), and travel permeability (Larkin et al. 2004). Collectively, and regardless of scale, these 3 variables integrate landscape and anthropogenic variables into a model that can successfully predict spatial distribution of HBI in Missoula.

The only variable not incorporated into the final multivariate model was distance to small-forested areas. In our study area, these areas mostly encompassed small forest patches on the edge of town and naturally forested parks within city limits, similar to high human disturbance land noted for its medium resistance to bear permeability (Larkin et al. 2004). Our assumption that these small forest patches would contribute to the location of HBI differently than large patches was correct; however, we assumed that these forest patches would be important escape cover in between foraging bouts within the urban area (Pelton 2000), thus a significant predictor of HBI. Our hypothesis was not supported, and small forest patches have less effect on HBI relative to other explanatory variables. This finding suggests that land planners developing urban areas may not need to account for HBI when developing semi-natural urban parks or reserves near urban areas (Niemelä 1999), unless those small areas are connected to large forest patches. Features such as housing density and proximity to large forest patches and major rivers and streams, however, are more important when planning urban areas.

The ability to identify areas (or clusters) with high probability of human–wildlife conflict has enabled appropriate management and mitigation methods to be applied strategically (Tourenq et al. 2001). With this information, specifically for HBI, wildlife managers can use different proactive management strategies depending on the area. In areas with a low probability of interaction, education programs can be developed to increase awareness and biological knowledge regarding bears. In areas with a moderate probability of interaction, education programs can be developed with specific attractant-reducing goals (e.g., use bear resistant dumpsters, use bird feeders seasonally, pick ripe fruit off of trees; Gore et al., 2006, 2008). Finally, in areas with a high probability of interaction, managers can implement not only education programs but also ordinances outlawing human behaviors that provide available attractants including garbage, fruit trees, and bird feeders (Peine 2001). The ability to strategically direct different management options in different areas contributes to efficient allocation of resources to proactively minimize human–wildlife interactions.

Although internal validation tests suggest our final model is good (Figs. 3 and 4), we recognize that our model assumptions may not have been fully met based on 2 issues with using noninvasive, public phone-call data. First, there are errors associated with geocoding residential mailing addresses into global positioning system coordinates (Rushton et al. 2006). For example, geocoding error is inversely related to population density, and 95% of errors can be as far as 152 m from true locations (Cayo and Talbot 2003). Second, data collection and entry inconsistencies can exist, also integrating error into estimates. Records sometimes are not screened by the same administrator prior to being entered, and interactions are documented by many managers who record information differently. Assuming these errors are normally distributed and thus not biased, we are confident in our findings. Furthermore, we minimized errors by collecting data from only one regional office of MFWP (i.e., 1 bear manager, <3 biologists, and <3 game wardens) minimizing the number of people entering and collecting information, and we manually reviewed all records in the database minimizing error from mistakes during data entry.

MANAGEMENT IMPLICATIONS

Our modeling framework and selected variables can be used to estimate the probably of HBI in developed and undeveloped areas. In developed areas, our model parameters can be estimated to stratify into sections of low to high probability of interaction, allowing strategic implementation of different proactive management activities (from promoting awareness to creating ordinances to eliminate attractants) across the areas of conflict opportunity. In undeveloped areas, wildlife managers involved in planning community development can integrate proposed housing development information into a future model, allowing estimation of the relative probability of future HBI. Hypothetical changes to housing development proposals can be incorporated, and the development plan with the lowest probability of HBI can be recommended. Management agencies should also systematically record human–bear sightings and interactions reported by the public. Current protocols may need to be strengthened, but these monitoring efforts are not difficult to develop (Gore et al. 2006, Baruch-Mordo et al. 2008). Information specific to developing spatially explicit models should be carefully documented such as the actual location of the sighting, not just the resident's address. With careful data collection, precise estimates of the relative probability of HBI will allow for more efficient and strategic management directives in the future.

ACKNOWLEDGMENTS

We thank B. Kohl for geocoding all human–black bear interaction locations, and we thank MFWP for cooperation and logistical assistance. M. S. Mitchell and J. Berger reviewed earlier versions of the manuscript. This study was supported by the Boone and Crockett Program in Wildlife Conservation and the Harry Longwell Family Foundation.

LITERATURE CITED

Ambarli H., and C. C. Bilgin. 2008. Human–brown bear conflicts in Artvin, northeastern Turkey: encounters, damage, and attitudes. Ursus 19:146–153.

Badyaev, A. V. 1998. Environmental stress and developmental stability in dentition of the Yellowstone grizzly bears. Behavioral Ecology 9:339–344.

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.

Beckmann J. P., and J. Berger. 2003. Using black bears to test ideal-free distribution models experimentally. Journal of Mammalogy 84:594–606.

Beckmann, J. P., C. W. Lackey, and J. Berger. 2004. Evaluation of deterrent techniques and dogs to alter behavior of "nuisance" black bears. Wildlife Society Bulletin 32:1141–1146.

Booth, M. M. 2005. Determining residents attitudes toward black bear management in the rattlesnake neighborhood: Missoula, Montana. Thesis, University of Montana, Missoula, USA.

Boyce, M. S., P. R. Vernier, S. E. Nielsen, and K. A. Schmiegelow. 2002. Evaluating resource selection functions. Ecological Modelling 157:281–300.

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.

Brodeur, V., J. Ouellet, R. Courtois, and D. Fortin. 2008. Habitat selection by black bears in an intensively logged boreal forest. Canadian Journal of Zoology 86:1307–1316.

Cayo M. R., and T. O. Talbot. 2003. Positional error in automated geocoding of residential addresses. International Journal of Health Geographics 2:10.

Conover, M. R. 2002. Resolving human–wildlife conflicts: the science of wildlife damage management. CRC Press, Boca Raton, Florida, USA.

Fecske, D. M., R. E. Barry, F. L. Precht, H. B. Quigley, S. L. Bittner, and T. Webster. 2002. Habitat use by female black bears in western Maryland. Southeastern Naturalist 1:77–92.

Ferraro P. J., and S. K. Pattanayak. 2006. Money for nothing? A call for empirical evaluation of biodiversity conservation investments. PLoS Biology 4:e105.

Goldberg, D. W., J. P. Wilson, C. A. Knoblock, B. Ritz, and M. G. Cockburn. 2008. An effective and efficient approach for manually improving geocoded data. International Journal of Health Geographics 7:60.

Gore, M. L., B. A. Knuth, P. D. Curtis, and J. E. Shanahan. 2006. Education programs for reducing American black bear–human conflict: indicators of success? Ursus 17:75–80.

Gore, M. L., B. A. Knuth, C. W. Scherer, and P. D. Curtis. 2008. Evaluating a conservation investment designed to reduce human–wildlife conflict. Conservation Letters 1:136–145.

Hopkins, J. B., S. Herrero, R. T. Shideler, K. A. Gunther, C. C. Schwartz, and S. T. Kalinowski. 2010. A proposed lexicon of terms and concepts for human–bear management in North America. Ursus 21:154–168.

Hosmer, D. W., and S. Lemeshow. 2000. Applied logistic regression. Second edition. John Wiley & Sons, New York, New York, USA.

Huberty, C. J. 1994. Applied discriminant analysis. Wiley Interscience, New York, New York, USA.

Johnson, C. J., S. E. Nielsen, E. H. Merrill, T. L. McDonald, and M. S. Boyce. 2006. Resource selection functions based on use–availability data: theoretical motivation and evaluation methods. Journal of Wildlife Management 70:347–357.

Jonkel C. J., and I. M. Cowan. 1971. The black bear in the spruce–fir forest. Wildlife Monographs 27.

Keating K. A., and S. Cherry. 2004. Use and interpretation of logistic regression in habitat-selection studies. Journal of Wildlife Management 68:774–789.

Kleckner, C. 2001. A study of urban black bear (*Ursus americanus*) distribution in the Anchorage area of southcentral Alaska. Thesis, University of Alaska Anchorage, USA.

Kretser, H. E., P. J. Sullivan, and B. A. Knuth. 2008. Housing density as an indicator of spatial patterns of reported human–wildlife interactions in Northern New York. Landscape and Urban Planning 84:282–292.

Larkin, J. L., D. S. Maehr, T. S. Hoctor, M. A. Orlando, and K. Whitney. 2004. Landscape linkages and conservation planning for the black bear in west-central Florida. Animal Conservation 7:23–34.

Manly, B. F. J., L. L. McDonald, D. L. Thomas, T. L. McDonald, and W. P. Erickson. 2002. Resource selection by animals: statistical analysis and design for field studies. Second edition. Kluwer, Boston, Massachusetts, USA.

Michalski, F., R. L. P. Boulhosa, A. Faria, and C. A. Peres. 2006. Human–wildlife conflicts in a fragmented Amazonian forest landscape: determinants of large felid depredation on livestock. Animal Conservation 9:179–188.

Montana Natural Resources Information System. 2009. Montana cadastral mapping project. <http://nris.state.mt.us>. Accessed 1 Sep 2009.

Niemelä J. 1999. Ecology and urban planning. Biodiversity and Conservation 8:119–131.

Peine, J. D. 2001. Nuisance bears in communities: strategies to reduce conflicts. Human Dimensions of Wildlife 6:223–237.

Pelton, M. R. 2000. Black bear. Pages 389–408 *in* S. Demaris and P. R. Krausman, editors. Ecology and management of large mammals in North America. Prentice–Hall, Upper Saddle River, New Jersey, USA.

Pyke, G. H., H. R. Pulliam, and E. L. Charnov. 1977. Optimal foraging: a selective review of theory and tests. The Quarterly Review of Biology 52:137–154.

Rushton, G., M. P. Armstrong, J. Gittler, B. R. Greene, C. E. Pavlik, M. M. West, and D. L. Zimmerman. 2006. Geocoding in Cancer Research: A Review. American Journal of Preventative Medicine 30:S16–S24.

Sitati, N. W., M. J. Walpole, R. J. Smith, and N. Leader-Williams. 2003. Predicting spatial aspects of human–elephant conflict. Journal of Applied Ecology 40:667–677.

Spencer, R. D., R. A. Beausoleil, and D. A. Martorello. 2007. How agencies respond to human–black bear conflicts: a survey of wildlife agencies in North America. Ursus 18:217–229.

Soul,é M. E. 1991. Land use planning and wildlife maintenance: guidelines for conserving wildlife in an urban landscape. Journal of American Planning Association 57:313–323.

Tourenq, C., S. Aulagnier, L. Durieux, S. Lek, F. Mesleard, A. Johnson, and J. Martin. 2001. Identifying rice fields at risk from damage by the greater flamingo. Journal of Applied Ecology 38:170–179.

U.S. Census Bureau. 2000. Census 2000 summary file 1. Census Bureau, Washington, D.C., USA.

U.S. Census Bureau. 2009. Topologically Integrated Geographic Encoding and Referencing System. <http://www.census.gov/geo/www/tiger/>. Accessed 30 Jul 2009.

USDA Forest Service. 2006. Vegetation Mapping Project. <http://www.fs.fed.us/r1/gis/vmap_v06.htm>. Accessed 30 Jul 2009.

Verbyla D. L., and J. A. Litvaitis. 1989. Resampling methods for evaluating classification accuracy of wildlife habitat models. Environmental Management 13:783–787.

Western Regional Climate Center. 2008. Historical climate information. Period of Record Monthly Climate Summary for Missoula 2 NE, Montana. Western Regional Climate Center, Reno, Nevada, USA. <http://www.wrcc.dri.edu>. Accessed 25 Mar 2008.

Wiens, J. A. 1989. Spatial scaling in ecology. Functional Ecology 3:385–397.

Wilson, S. M., M. J. Madel, D. J. Mattson, J. M. Graham, and T. Merrill. 2006. Landscape conditions predisposing grizzly bears to conflicts on private agricultural lands in the western USA. Biological Conservation 130:47–59.

Worton, B. J. 1989. Kernel methods for estimating the utilization distribution in home-range studies. Ecology 70:164–168.

Young D. D., and J. J. Beecham. 1986. Black bear habitat use at Priest Lake, Idaho. Bears: Their Biology and Management 6:73–80.

Zack, C. S., B. T. Milne, and W. C. Dunn. 2003. Southern oscillation index as an indicator of encounters between humans and black bears in New Mexico. Wildlife Society Bulletin 31:517–520.

Associate Editor: Michael J. Chamberlain.