Exurban Land Use Facilitates Human-Black Bear Conflicts

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ABSTRACT The distribution and arrangement of habitats and human use areas are important to understanding where and why conflicts with wildlife occur; such data may inform proactive management activities to minimize conflicts. Black bear (Ursus americanus) abundance and the number of human-black bear conflicts are increasing in the northeast United States, particularly in developed areas. We applied a spatial modeling approach to identify landscape variables associated with the spatial intensity of human-black bear conflicts in Connecticut, and predicted where conflicts are most likely in the future. Percent forest cover within 1 km² and the proportion of such forest classified as edge habitat were the most important factors associated with the location of conflicts. We attribute this result to Connecticut’s exurban landscape, typical of New England, in which housing and natural land cover are extensively interspersed, as opposed to housing fragmenting natural land cover. This finding can inform town planners and developers in designing future housing to proactively minimize human-black bear conflicts. We also identified areas at high risk for conflict. The extent of these areas will help determine the scale of bear management units within which different management approaches are applied. © 2014 The Wildlife Society.

KEY WORDS black bears, Connecticut, human dimensions, spatial, prediction, wildlife conflicts.

The unique landscapes represented by exurban development bring wildlife into close proximity with humans, increasing the potential for conflict. Land-use pattern in Connecticut is typical of New England, with the state comprised almost entirely of exurban housing (Theobald 2001). Concurrently, black bear (Ursus americanus) abundance is increasing throughout the northeast United States, and their range has expanded into Connecticut. The interspersion of forest and housing in the state, and bears’ ability to exploit human food sources simultaneously facilitate human-black bear conflicts, and present substantial challenges to conflict management.

Exurban development patterns (6–25 homes/km²) are characterized by housing densities between rural and urban embedded within natural cover types, and were the fastest growing form of land use in the United States as of 2000 (Brown et al. 2005). Such development may have strong effects on biodiversity and biological communities, with specific impacts varying among species (Hansen et al. 2005). Human development has historically been thought to displace native wildlife (Vogel 1989, Theobald et al. 1997). However, exurban land-use patterns produce a more multidimensional human–wildlife interface, as interspersion of housing and native vegetation benefits some human-adapted guilds (Miller and Hobbs 2002, Glennon and Porter 2005, Hansen et al. 2005).

As opportunistic omnivores, black bears may readily adapt to, and thrive in, forested exurban and suburban areas. Although black bears may be sensitive to large-scale anthropogenic removal of natural habitat (Mattson 1990, Brodeur et al. 2008), housing interspersed within forest provides additional food sources that bears exploit (Ranglack et al. 2009, Baruch-Mordo et al. 2014). In many developed areas, black bears have significantly modified their foraging and reproductive behavior because of the regular availability and abundance of anthropogenic foods (Beckmann and Berger 2003, Ellingwood 2003, MacKenzie 2003, Moyer et al. 2007, Beckmann and Lackey 2008). In addition to providing consistently available foods, housing within suitable bear habitat may accelerate the rate and extent of bear habituation to humans (McCullough 1982).

However, the majority of this research has focused on rural areas where livestock depredation was the primary form of conflict (Bradley and Pletscher 2005, Michalski et al. 2006, Wilson et al. 2006, Baruch-Mordo et al. 2008). Unlike the distinct boundaries between bear habitat and human land use found in such areas, exurban landscapes contain exploitable human food sources within a matrix of relatively natural bear habitat. Therefore, the proximity of habitat and housing may be less important in determining the distribution of conflicts than landscape variables describing their interspersion in exurban contexts.

Our first objective was to use public reports of black bear property damage to identify landscape factors that explain the spatial distribution of human-black bear conflicts in exurban Connecticut. We then used these factors to predict relative risk of conflict across the state to identify potentially high-risk areas. We hypothesized that Connecticut’s exurban housing patterns would result in the spatial distribution of human-black bear conflicts being related to variables associated with the level of integration of housing and forest. Our second objective was to address the effect of demographic variability and reporting bias implicit in using citizen reports (Howe et al. 2010) to understand the spatial distribution of human–wildlife conflict.

**STUDY AREA**

Human-bear conflicts were most frequent in northwestern Connecticut (Fig. 1). Connecticut had a population of 3,590,347 people about the time of our study (U.S. Census 2012). Connecticut’s landscape was largely forested (Fig. 2a), with 58.8% of land cover in the state forest according to the 2006 National Land Cover Database (NLCD; Fry et al. 2011). Mean housing density in Connecticut was 5.18 houses/ha, with most urban development concentrated along the coast and the U.S. Interstate 91 corridor (Fig. 2b). Outside of high density urban areas, housing in Connecticut was dispersed and perforated the forest canopy. 51.7% of the state was categorized as intermixed (i.e., >1 house/16 ha and >50% forest cover) according to the Wildland Urban Interface classification (Radeloff et al. 2005).

We restricted analyses to a 4-km buffer surrounding locations of reported human-bear conflict. A 4-km radius corresponds to a circle of roughly 50 km². The median female home range size for Connecticut black bears is about 30 km² (Connecticut Department of Energy and Environmental Protection, unpublished data); therefore, this buffer restricted the study extent to an area of the state where bears are regularly reported to occur.

**METHODS**

The Connecticut Department of Energy and Environmental Protection (DEEP) documented all black bear incidents in a formal database. These include citizens’ sightings, reports of property damage, and vehicle collisions. Because our objective was to describe the spatial distribution of conflicts between bears and humans, we excluded all reports of bear sightings and considered only reports involving nuisance behavior (e.g., damaging property, eating garbage, etc.) for analysis. We used the address locator function in ArcView 10.1 (Environmental Systems Research Institute, Inc., Redlands, CA, USA) to obtain coordinates from addresses associated with conflict records occurring during 2008–2012.

![Figure 1. Human-black bear conflict locations reported to Connecticut Department of Energy and Environmental Protection from 2008 to 2012. Borders for all 166 Connecticut towns are displayed, which may appear similar to county lines in other states.](image)
This function generates a match score, which indicates how well input addresses match candidate locations. We manually located reports with <70% match score using aerial photography cross-referenced with Google Earth (Google, Mountain View, CA, USA) imagery. We similarly cross-referenced the location of a random sample of 100 points to compare the spatial accuracy of automated geocoding to the actual location of buildings at incident addresses. We determined the percentage of geocoded incidents that fell within 30 m of buildings, because this distance corresponds to the cell size of rasters associated with predictor variables. Hereafter, these locations are referred to as conflict locations.

We used multiple regression to evaluate relationships between landscape characteristics and conflict locations in a resource utilization framework, using a kernel estimate of the intensity of conflicts as the response variable (Millspaugh et al. 2006). We created conflict intensity surfaces using kernel density estimation in Geospatial Modeling Environment (GME version 0.7.2.1, www.spatialecology.com/gme, accessed 10 Oct 2014). We calculated kernel surfaces using least squares cross-validation (LSCV) selected bandwidth, as well as fixed bandwidths of 1 km and 5 km. We chose the appropriate bandwidth using correlations between the resulting intensity surface and univariate predictor variables, selecting the surface with the highest correlation coefficients ($R$). Kernel intensity surfaces and all predictor variables were represented in 30 × 30-m pixel rasters.

We performed a 2-stage analysis to identify significant natural landcover predictors of conflict intensity, and then to assess the additional explanatory value of anthropogenic variables. We first constructed a set of a priori candidate models composed of variables related to the abundance and configuration of natural bear habitat. These included distance (km) to forest, percent forest cover, forest edge density (as an indicator of forest fragmentation; Powell et al. 1997, Brodeur et al. 2008, Baldwin and Bender 2012),

Figure 2. 2006 National Landcover Database (NLCD) landcover and 2005 Wildland-Urban Interface (WUI) classification for Connecticut showing (a) predominant forest cover in green and (b) intermixed land use (>1 house/16 ha and >50% forest cover) in yellow.

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distance (km) to all streams and main stem streams, and distance (km) to wetlands (riparian vegetation; Young and Beecham 1986, Fecske et al. 2002).

To calculate distances to forest and wetlands, we reclassified the 2006 NLCD raster into 2 binary raster layers. The first combined deciduous, coniferous, and mixed forest classes into a single forest class, from which we created a raster layer depicting distance to the nearest forest. The second binary raster combined forested and emergent wetland into a single wetland class, which we used to create a distance to wetland raster. We estimated forest edge density as the percentage of forest cover within 100 m of non-forest cover types within 0.0625-km², 0.25-km², and 1-km² windows. We calculated percent cover of forested land at a given location within identical windows. We calculated distance from main stem and all streams using the Connecticut DEEP 2005 hydrography shapefile.

We used univariate linear regression models to select the most useful representation of streams (all streams, or main stem) and the window size for quantifying forest cover and forest edge density. We selected the best models representing the effect of streams, forest cover, and edge density on conflict intensity using Akaike’s Information Criterion (AIC; Akaike 1974, Burnham and Anderson 2002). Distance to main stem streams, and a 1-km² window characterization of forest cover and forest edge density had the lowest AIC scores (see Table S1, available online at www.onlinelibrary.wiley.com). We then used these variable representations in multivariate models.

We used scatterplots to identify potentially non-linear univariate relationships between predictor variables and conflict intensity. Percent forest cover, edge density, distance to streams, and distance to wetlands appeared to have quadratic relationships with conflict intensity, and we subsequently compared models with quadratic representations of each of these variables to untransformed models using AIC scores. We selected quadratic representations of percent forest cover and wetland distance for inclusion in multivariate models, because quadratic models had the lowest AIC values and univariate linear models were not competing (i.e., within 2 AIC units; see Table S2, available online at www.onlinelibrary.wiley.com). We assessed all predictors for collinearity (r > 0.5) using a Pearson’s correlation matrix, eliminating 1 variable from any collinear pair.

We tested candidate models that included natural habitat variables to explore hypotheses that riparian vegetation (wetland, stream), forest configuration (% forest, % edge), and both forest and riparian habitat (% forest, % edge, wetland, stream) explained the spatial intensity of conflicts. We constructed models containing each of the above sets of variables and distance to forest to assess the relative importance of forest structure versus forest proximity based on AIC score. We hypothesized this to be an important distinction in exurban contexts for identifying conflict areas. We refer to these models as natural habitat models.

We constructed a second set of candidate models including all variables from the top-ranked natural habitat model and additional anthropogenic variables. Anthropogenic variables included housing density (Krester et al. 2008, Merkle et al. 2011) and median household income. We obtained data for both variables from the 2007–2011 United States Census (U.S. Census Bureau 2011). The density of houses represented the opportunity for conflict and may explain spatial conflict intensity beyond the presence of natural bear habitat. The socioeconomic level of neighborhoods might affect conflict intensity through the presence of unique bear attractants or as a representation of differences in attitudes toward wildlife.

We initially fit generalized linear models with Gaussian error structures and an identity link function using the GLM command in the R language and environment for statistical analyses (R Version 2.15.2, www.r-project.org, accessed 14 Sep 2013). We tested model residuals at conflict locations for global spatial autocorrelation using Moran’s I, and local spatial autocorrelation using local Moran statistics in the program GeoDa (GeoDa Version 1.6.0, http://geodacenter.asu.edu, accessed 15 Sep 2013). We subsequently evaluated the ability of spatial lag and spatial error regression to improve multivariate model fit using Lagrange Multiplier (LM) statistics in GeoDa. In all cases, spatially lagged and spatial error regression improved fit over ordinary regression, as indicated by LM tests with P ≤ 0.001 for all candidate models (see Table S3, available online at www.onlinelibrary.wiley.com). We additionally performed the same 2-stage analysis on our candidate model sets using spatial error multivariate regression. This approach accounts for spatial autocorrelation in the error term as a nuisance parameter, allowing for better estimation of the beta parameters of interest. We identified models with the greatest support as those receiving the lowest AIC score among the candidate set. We report and discuss the results of those spatial error regression analyses, hereafter referred to as spatial models.

Spatially explicit models and local autocorrelation analyses in GeoDa require specification of a neighborhood distance. We defined neighborhoods as the distance within which conflict locations exhibited spatial clustering. We estimated the nearest neighbor distance distribution function using the Gist command in the spatstat package (Baddeley and Turner 2005) for program R, and compared the observed distribution of nearest neighbor distances between conflict locations to the distributions generated by simulated random point patterns. The distance at which the observed distribution for conflict locations fell within the 99% confidence envelope of simulated distributions was 1,500 m, indicating locations closer than 1,500 m were more clustered than at random. We therefore used an equal weight matrix defining all conflict locations within 1,500 m as neighbors in spatial models and for local autocorrelation analysis.

We evaluated predictive ability of best fitting models on the original data using K-folds cross validation (Boyce et al. 2002). We first divided the data into 10 20% testing and 80% training sets. We partitioned predicted conflict intensity for testing data into 10 equal bins, ranked from high to low, and compared these to the number of actual conflict locations within each bin using Spearman’s rank correlation (Boyce
et al. 2002). We used variables and coefficients from the top ranked spatial model, which estimated the relationship between variables and conflict intensity after accounting for autocorrelation in locations, to produce a statewide map of predicted conflict intensity, illustrating high and low risk areas.

RESULTS

We spatially referenced 1,589 reports of black bear damage occurring during 2008–2012 (Fig. 1). Of the random sample of 100 spatially referenced points, 88% were within 30 m of actual structures at the specified address, indicating sufficient location accuracy. Income, distance to wetland, distance to main stem streams, housing density, distance to forest, forest edge density, and percent forest cover were significant univariate predictors (i.e., \( P < 0.05 \)) based on Wald’s Chi-square test. Correlations among these variables ranged from \( r = -0.38 \) to \( r = 0.35 \). Forest edge density and percent forest cover were correlated within 0.0625-km² (\( r = 0.63, P = 0.03 \)) and 0.25-km² (\( r = 0.58, P = 0.08 \)) windows. However, they were not collinear as calculated at the 1-km² window scale (\( r = 0.26, P < 0.001 \)), which we previously identified as the best characterization for these variables based on AIC score. We selected a bandwidth of 5 km for kernel density estimation because it produced an intensity surface with the strongest correlations to potential predictor variables of those tested.

The natural habitat model including variables describing both forest and riparian area effects had the lowest AIC score and no other models were competing (i.e., \( \Delta \text{AIC} > 2 \)). This top-ranked model indicated that increased forest edge density, intermediate percent forest cover, intermediate distance to wetlands, and proximity to streams were predictors of conflict locations in Connecticut (Table 1). Distance to forest edge was not included in the top-ranked model, and all models containing percent forest cover and edge density were more supported without distance to edge (Table 1). Percent forest cover was quadratically related to conflict intensity, such that an intermediate amount of forested land (42%) was associated with the highest intensity of conflict. At low forest cover, our top-ranked model predicted an increase of 0.03 km² of forest to increase conflict intensity by 1 conflicts/km². Similarly, an increase in forest edge of 13.2% corresponded to an additional 1 conflicts/km².

A model containing housing density in addition to variables in the top-ranked natural habitat model received the greatest AIC support (Table 1), and we found a positive relationship between the density of houses and conflict intensity (Table 2). An additional 3,874 houses/km² was predicted to increase conflict intensity by 1 conflicts/km². Although not the top model, an anthropogenic model with housing density and household income was moderately supported (Akaike weight, \( \omega_{\text{AIC}} = 0.17 \)) and received a lower AIC score than the top-ranked natural habitat model (Table 1). Additionally, the top-ranked non-spatial regression model included the same set of predictor variables as the top-ranked spatial model but also indicated a positive relationship with median household income, in which high income census tracts were associated with conflict locations (\( \beta = 8.15 \times 10^{-7}, P \leq 0.001 \)).

Residuals produced by the best spatial model had low global autocorrelation among all conflict locations (\( I = 0.099, P < 0.001 \)). Additionally, only 4% of locations showed significant local autocorrelation within 1,500 m of neighborhoods. Cross validation indicated that the top-ranked spatial model provided good prediction for the spatial distribution of conflicts in Connecticut (\( r_s = 1, P \leq 0.001 \)). Using coefficients from the most supported spatial model, we report Akaike’s Information Criterion (AIC), relative difference in AIC value compared to the top-ranked model (\( \Delta \text{AIC} \)), AIC model weight (\( \omega \)), and the number of model parameters (K).

### Table 2. Parameter estimates (β) and standard error (SE) for significant predictor variables in top-ranked spatial model of human-black bear conflicts in Connecticut during 2008–2012.

<table>
<thead>
<tr>
<th>Variable</th>
<th>β</th>
<th>SE</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td>Edge density</td>
<td>0.014</td>
<td>0.004</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Forest cover</td>
<td>0.067</td>
<td>0.009</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Forest cover²</td>
<td>-0.044</td>
<td>0.009</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Distance to main stream (m)</td>
<td>4.96E-04</td>
<td>1.55E-04</td>
<td>0.001</td>
</tr>
<tr>
<td>Distance to wetland (m)</td>
<td>0.00267</td>
<td>8.76E-04</td>
<td>0.002</td>
</tr>
<tr>
<td>Distance to wetland² (m)</td>
<td>-3.99E-04</td>
<td>1.56E-07</td>
<td>0.01</td>
</tr>
<tr>
<td>House density</td>
<td>2.74E-06</td>
<td>1.01E-06</td>
<td>0.007</td>
</tr>
</tbody>
</table>

### Table 1. Summary of spatial model-selection procedure examining variables affecting spatial intensity of human-black bear conflicts in Connecticut during 2008–2012. We report Akaike’s Information Criterion (AIC), relative difference in AIC value compared to the top-ranked model (\( \Delta \text{AIC} \)), AIC model weight (\( \omega \)), and the number of model parameters (K). Variables included percent forest cover within 1 km² (%Forest), proportion of forest edge within 1 km² (%Edge), distance to wetlands (Wet), distance to streams (Stream), distance to forest (ForDist), housing density (Housing), and household income (Income). All models included an autoregressive term that is not displayed in the table.

<table>
<thead>
<tr>
<th>Model</th>
<th>K</th>
<th>AIC</th>
<th>ΔAIC</th>
<th>( \omega )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Natural habitat + anthropogenic</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Forest, (%Forest)², %Edge, Wet, Wet², Stream, Housing</td>
<td>8</td>
<td>-24,237.9</td>
<td>0</td>
<td>0.73</td>
</tr>
<tr>
<td>%Forest, (%Forest)², %Edge, Wet, Wet², Stream, Housing, Income</td>
<td>9</td>
<td>-24,235.0</td>
<td>2.9</td>
<td>0.17</td>
</tr>
<tr>
<td>%Forest, (%Forest)², %Edge, Wet, Wet², Stream</td>
<td>7</td>
<td>-24,232.6</td>
<td>5.3</td>
<td>0.05</td>
</tr>
<tr>
<td>%Forest, (%Forest)², %Edge, Wet², Stream, Housing</td>
<td>8</td>
<td>-24,234.2</td>
<td>5.5</td>
<td>0.05</td>
</tr>
<tr>
<td>Natural habitat</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>%Forest, (%Forest)², %Edge, Wet, Wet², Stream</td>
<td>7</td>
<td>-24,232.6</td>
<td>0</td>
<td>0.86</td>
</tr>
<tr>
<td>%Forest, (%Forest)², %Edge, Wet, Wet², Stream, ForDist</td>
<td>8</td>
<td>-24,229.9</td>
<td>3.7</td>
<td>0.14</td>
</tr>
<tr>
<td>%Forest, (%Forest)², %Edge</td>
<td>4</td>
<td>-24,219.2</td>
<td>13.4</td>
<td>0.001</td>
</tr>
<tr>
<td>%Forest, (%Forest)², %Edge, ForDist</td>
<td>5</td>
<td>-24,218.5</td>
<td>15.1</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Wet, Wet², Stream, ForDist</td>
<td>5</td>
<td>-24,202.0</td>
<td>30.6</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Wet, Wet², Stream</td>
<td>4</td>
<td>-24,174.4</td>
<td>58.2</td>
<td>&lt;0.001</td>
</tr>
</tbody>
</table>

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the distribution of predicted human-black bear conflict intensities across Connecticut, given statewide occupancy by black bears, indicate low risk of conflict in urbanized areas (i.e., central and coastal Connecticut), and relatively high risk in forested population centers (i.e., western Connecticut; Fig. 3).

**DISCUSSION**

Human development interspersed within forested habitat facilitated contact between bears and humans in Connecticut, with conflict locations best explained by amount of forest cover and edge density. We attribute this pattern to the high level of housing dispersed within Connecticut’s continuously forested landscape. Proximity of forest patches was not important in predicting conflict locations in Connecticut. We also found evidence that the rate of bear damage reporting may differ among neighborhoods according to socioeconomic status, based on the inclusion of census tract median household income in a moderately supported spatial model and the top-ranked ordinary regression model. We conclude that land use patterns strongly affect the spatial distribution of human-black bear conflicts in exurban contexts such as Connecticut.

Intermediate percent forest cover was associated with the highest probability of conflict occurrence, with low probability of conflicts in places with little forest cover (e.g., downtown Torrington) or in places with large tracts of forest (Fig. 3). Intuitively, as the amount of forest surrounding a given location increases from 0, the probability of human-bear conflicts is expected to rise as a function of greater overlap between bear habitat and human housing. We found conflict probabilities declined at high forest coverage after an intermediate maximum (42% forest cover). The inclusion of percent forest edge, which is an indicator of forest fragmentation, in the top-ranked model suggested that a description of forest configuration is needed in addition to total amount to explain variation in conflict probabilities across locations (Table 1).

Increased forest edge density increased the likelihood of conflict. In rural and undeveloped landscape contexts, fragmented forests can promote bear presence by providing multiple food sources associated with habitat mosaics and edges (Baldwin and Bender 2012), and bears may simply be more likely to frequent these areas in Connecticut. However, exurban forest edges are created in large part by human development. In Connecticut, 68% of all non-forested land is developed, with high edge density indicative of a development footprint on forested lands. This arrangement provides bears greater opportunity and access to anthropogenic foods and attractants relative to the same amount of forest cover consisting of less edge.

The relationships between forest cover, edge density, and conflict intensity are important to consider in the context of exurban development. This pattern of land use places housing within native habitats because natural landscapes are viewed by many homeowners as desirable (Rudzitis 1999, Rasker and Hansen 2000). This perforation creates an extensive interface between natural bear habitat and housing.
Our results demonstrated such land use patterns facilitate interactions between bears and humans in exurban areas. In Missoula, Montana, the probability of human-black bear conflict locations was positively related to intermediate housing density and proximity to large (>100 km²) forest patches (Merkel et al. 2011). Inconsistency in predictors between Connecticut and Montana likely reflects differences in land use patterns. Housing in Connecticut is typical of exurban land use, which perforates rather than fragments a continuous forest canopy (Fig. 2a). Much of the non-urban residential area in Connecticut included a predominance of intermixed (WUI classification) land use (Fig. 2b), indicating forest cover was ubiquitously distributed among housing (and vice versa). With houses located extensively within forests that are suitable bear habitat (Garshelis and Pelton 1981, Rogers and Allen 1987, Powell et al. 1997, Mitchell et al. 2002), the local abundance and structure of forest at a given location determined conflict intensity rather than forest proximity. Further, conflict intensity increased with housing density because these locations were largely surrounded by forest. In both Montana and Connecticut, conflicts between black bears and humans occurred at the interface of housing and natural land cover. Differences in significant predictors illustrate the importance of local land-use patterns in facilitating conflicts between humans and black bears.

We believe the positive effect of mean household income on the intensity of human-bear conflict in the most supported non-spatial model, and a spatial model with more support than the top-ranked natural habitat model, suggested residents of high-income areas had an increased propensity for reporting incidents. The reduced importance, as indicated by model weight, of income in spatial compared to non-spatial models suggests income may be associated with spatial autocorrelation of conflict locations—a result consistent with changes in rates of reporting. We reached this conclusion because although high-income areas may contain unique bear attractants such as orchards, vineyards, beehives, or livestock, only 2.5% of conflicts involved damage to these items, indicating such features did not play a major role in attracting bears to high income properties.

One possible explanation for increased reporting rates in high-income census tracts is the potentially high monetary value of damaged property in these areas. The cost of wildlife damage can decrease tolerance for wildlife on and around private property (Conover 1998), and generate demand for management efforts such as lethal control (Bangs and Shivik 2001, Decker et al. 2006, Muhly and Musiani 2009). Therefore, greater cost of bear damage could increase the likelihood of complaints. However, 82% of damage reports in Connecticut involved bears rummaging in garbage or destroying bird feeders, making damage expense an unlikely explanation for reporting rates.

Instead, we suggest that high-income areas in Connecticut may have lower black bear acceptance capacity (Decker and Purdy 1988). Previous studies have found that citizens’ perception and attitudes toward wildlife can vary according to a wide variety of social factors including demographics, occupation, education level, media exposure, and the nature of interactions with wildlife (Kaltenborn et al. 1999, Bright et al. 2000, Naughton-Treves et al. 2003, Gore et al. 2005, Don Carlos et al. 2009, Siemer et al. 2009). Public tolerance for wildlife is a function of the balance of perceived benefits and costs presented by wildlife populations (Conover 1998; West et al. 2002, Decker et al. 2006); therefore, bears are likely viewed as a potential risk with little benefit by residents of high-income census tracts. Our results highlight the potential need to consider spatial variation in stakeholder attitudes when making and evaluating black bear management decisions (Gore et al. 2006) because social carrying capacity may change over small spatial scales.

Variation in social carrying capacity will be important to consider when managing bears in an exurban context because of potentially opposing views toward management actions. For example, bear hunting can reduce human-bear conflicts by limiting the size of bear populations and re-enforcing wariness of humans (Brody and Pelton 1989, Mattson 1990). However, the institution of bear hunting can be a socially contentious issue (Harker and Bates 2007). In exurban and suburban contexts, hunting over bait may be the only applicable method to implement harvest (Hristienko and McDonald 2007) because of the relatively close spacing of housing, division of private lands, firearm discharge restrictions, and trespassing laws. If support of hunting for bear management changes at the scale of census tracts, localized decisions regarding acceptable methods will be needed to preserve its viability as a management option across a wider range of landscapes.

Likewise, high-risk areas with low support for lethal management can be targeted for education programs and local legislation aimed at modifying human behavior (e.g., town garbage ordinances). Such practices can be effective at preventing conflicts at localized scales (McCarthy and Seavoy 1994, Peine 2001), minimizing the need for responsive management actions (e.g., translocation and aversive conditioning) that can involve substantial resource requirements (Rauer et al. 2003). Identification of high-risk and high-demand areas would allow managers to focus human behavior modification strategies where there is the greatest potential for return on investment.

**MANAGEMENT IMPLICATIONS**

As black bear range continues to expand in the northeast United States, our model can be used to proactively reduce the potential for conflict between bears and humans by informing housing development and targeting preventative management actions. Housing built within natural settings is generally seen as an amenity of exurbia, but our results demonstrate this arrangement comes with increased risk of conflicts with bears. Our findings suggest that a more distinct segregation of forest cover and housing would likely reduce conflicts. These patterns should be considered in areas where minimizing bear damage is a high priority and/or opposition to management actions is strong. The variables associated with high conflict intensity identified in our model also indicate areas of Connecticut with high potential for
human-black bear conflict not yet reporting incidents. Such areas should be targeted for proactive measures such as public education programs and garbage ordinances, particularly those at the leading edge of bear range in Connecticut.

ACKNOWLEDGMENTS

We thank J.C. Vokoun, R. Jacobson, and C.D. Rittenhouse for manuscript review and comments. D.L. Civco provided guidance for GIS data manipulation and analyses. Funding provided by Federal Aid in Wildlife Restoration Act under Project W-49-R “Wildlife Investigations” administered by the Connecticut Department of Energy and Environmental Protection, Wildlife Division.

LITERATURE CITED


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