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Science of the Total Environment 341 (2005) 15–31

Science of the Total Environment
An International Journal for Scientific Research into the Environment and its Relationship with Humankind

www.elsevier.com/locate/scitotenv

The development of a spatially explicit model to estimate radiocaesium body burdens in raccoons (*Procyon lotor*) for ecological risk assessment

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Received 25 May 2004; received in revised form 27 August 2004; accepted 7 September 2004

Abstract

A spatially explicit model of raccoon (*Procyon lotor*) distribution for the U.S. Department of Energy's (DOE) Savannah River Site (SRS) in west-central South Carolina was developed using data from a raccoon radio-telemetry study and visualized within a Geographic Information System (GIS). An inductive approach was employed to develop three sub-models using the ecological requirements of raccoons studied in the following habitats: (1) man-made reservoirs, (2) bottomland hardwood/ riverine systems, and (3) isolated wetland systems. Logistic regression was used to derive probabilistic resource selection functions using habitat compositional data and landscape metrics. The final distribution model provides a spatially explicit probability (likelihood of being in an area) surface for male raccoons. The model is a stand-alone tool consisting of algorithms independent of the specific GIS data layers to which they were derived. The model was then used to predict contaminant burdens in raccoons inhabiting a riverine system contaminated with radiocaesium (^{137}Cs). The predicted ^{137}Cs burdens were less than if one would assume homogeneous use of the contaminated areas. This modelling effort provides a template for DOE managed lands and other large government facilities to establish a framework for site-specific ecological assessments that use wildlife species as endpoints.

Keywords: GIS; Raccoons (*Procyon lotor*); Radiocaesium; Resource selection functions; Risk assessment; Spatial modelling

1. Introduction

Understanding the fate and effects of environmental pollutants is an important concern, particularly when wildlife may act as vectors of contamination to

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doi:10.1016/j.scitotenv.2004.09.017

the food chain of humans or other predators. To properly quantify these potential risks, species must be studied and subsequently modelled at the landscape level (Cairns, 1993; Cairns and Niederlehner, 1996) using both population and individual level parameters (Akçakaya, 2001; Matsinos and Wolff, 2003). The North American raccoon (*Procyon lotor*) has seldom been considered for both ecological and human-based risk assessments, although it is commonly harvested and consumed throughout the southeastern United States (South Carolina Department of Natural Resources, 1996a,b,2000). Several characteristics of raccoons make them potential agents of contaminant movement and dispersal including: (1) high population levels with an extended range throughout North America in a variety of habitats, (2) their proclivity to travel extended distances (Glueck et al., 1988; Walker and Sunquist, 1997; Gehrt and Fritzell, 1998), (3) a propensity to utilize human-altered habitats in combination with an ability to move freely in and out of contaminated waste sites (Hoffmann and Gottschang, 1977; Clark et al., 1989; Khan et al., 1995), and (4) a broadly omnivorous diet which includes components of both terrestrial and aquatic food chains (Lotze and Anderson, 1979; Khan et al., 1995). However, the fact that raccoons are opportunistic omnivores, which hinders the ability to estimate their integrated trophic position and the fact that they occupy a variety of habitats, has severely complicated interpretations of contaminant uptake patterns (Gaines et al., 2002).

For these reasons, the U.S. Environmental Protection Agency (EPA) and other organisations like the U.S. Department of Energy (DOE) have avoided using raccoons as indicator species for ecological risk assessments. This species has been well studied on the DOE's Savannah River Site (SRS) and recently, through stable isotopic analyses, the relative trophic positions occupied by different raccoon populations has been quantified and correlated with contaminant burdens shown by this species at this site (Gaines et al., 2002). With these key pieces of information, researchers can now use raccoons as focal species for ecological risk assessments. To accomplish this, the probability that a raccoon may occupy a particular habitat or ecosystem must be established. Using these parameters, exposure and uptake estimates can be refined to better predict what the contaminant burden might be in an individual occupying a habitat mosaic within a contaminated area (Sample and Suter, 1994). Past modelling efforts have shown that home range size alone can have a dramatic effect on exposure and uptake estimates and that although larger home ranges decrease predicted contaminant burdens, they also lead to a higher probability of extreme exposures (Marinussen and van der Zee, 1996). These probabilities can be modelled when both the home range size and probability of an organism occupying a contaminated region are taken into consideration. Here, such a model is presented that predicts male raccoon distribution on the SRS using probabilistic resource selection functions. Although the assimilation and depuration rates of contaminants in raccoons may not necessarily be linearly related to their proportional use of contaminated habitats, our approach represents a first step to demonstrate how uptake models can be established and then later refined for quantitative risk assessments. Specifically, this raccoon distribution model was applied to predict the relative body burden of male raccoons inhabiting a stream system contaminated with radiocaesium (^{137}Cs) that borders a private hunting ground outside of the SRS boundary. Three different body burden estimates were predicted based on three consecutive yearly raccoon harvests near this hunting ground. These body burdens were then used to calculate a human-based risk assessment for those individuals who may consume raccoon meat from such animals. These results were then considered in terms of ecological risk assessment.

2. Study areas

The SRS is an 804 km^2 former nuclear production and current research facility located in west-central South Carolina, USA (33.1°N, 81.3°W; Fig. 1) that has been closed to public access since 1952. In 1972, the SRS was designated as the nation's first National Environmental Research Park to provide land where basic ecology and human impacts on the environment could be studied (White and Gaines, 2000). Raccoons that were used for movement studies described below were collected from three locations on the SRS. These locations were chosen to represent the typical ecosystems in which this species resides. Specifically, this

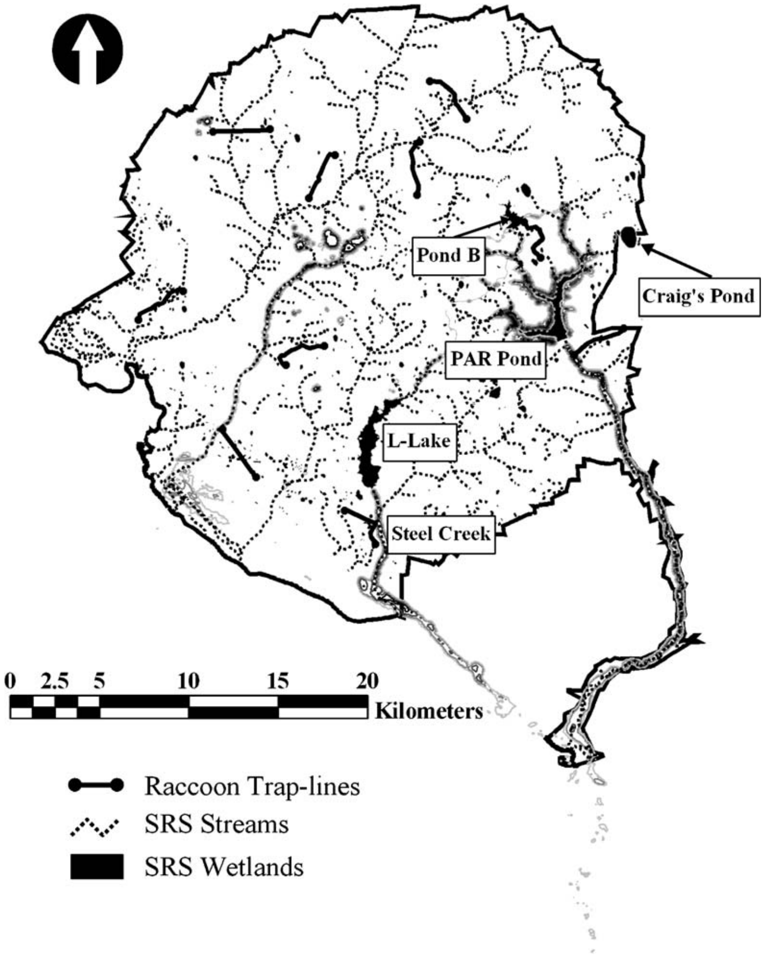

Fig. 1. Map of the Department of Energy's Savannah River Site showing areas where raccoons were tracked (Pond B, Steel Creek, and Craig's Pond) during the radio-telemetry study used to create the three raccoon distribution submodels. Raccoon trap-lines used for model validation are shown along with radiocaesium (^{137}Cs) isopleths.

species tend to favour aquatic riparian areas, rather than mesic upland areas (Lotze and Anderson, 1979; Khan et al., 1995). Raccoons were collected from an 87-ha former reactor cooling reservoir (Pond B) and a disturbed stream flood-plain (Steel Creek) directly contaminated by ^{137}Cs releases. Both of these systems have been intensely studied with regard to the bioaccumulation of ^{137}Cs in resident flora and fauna (Brisbin et al., 1974a,b; Evans et al., 1983; Gladden et al., 1985; Brisbin et al., 1989; Whicker et al., 1990; Gaines et al., 2000). Pond B (part of the Par Pond reservoir system) received cooling water that was contaminated with ^{137}Cs from leaking reactor fuel elements. Although other small leakages occurred, the largest discharge of ^{137}Cs took place from 1963 to 1964 and amounted to 5.7×10^{12} Becquerels (Bq). This reservoir system originally received water and current water levels in Par Pond are maintained from the Savannah River, which borders the SRS.

The Steel Creek watershed drains into an inundated riverine swamp delta that is contiguous with the Savannah River (Fig. 1). Two production reactors discharged effluents into Steel Creek containing cooling water mixed with purge water from basins used to store irradiated reactor fuel and target assemblies. From 1954 through 1978, approximately 1.06×1013 Bq ^{137}Cs that leaked from defective experimental fuel assemblies were discharged into

Steel Creek via this purge water (Ashley and Zeigler, 1980).

A third location, Craig's Pond/Sarracenia Bay (hereafter Craig's Pond), was chosen as a typical Carolina bay ecosystem. Carolina bays are naturally occurring shallow elliptical wetland depressions (Lide, 1997) that provide ample food for raccoons. Most of these bays on the SRS are surrounded by forested areas that provide raccoon shelter. Craig's Pond is a 78.2-ha wetland depression that represents the largest open-water Carolina bay on the SRS (Davis and Janecek, 1997). The much smaller Sarracenia Bay (4.0 ha) is located approximately 200 m from Craig's Pond. There have been no reported direct inputs of ^{137}Cs or other contaminants into onsite areas of the Craig's Pond/Sarracenia Bay complex. Although a private company located next to the SRS, Chem Nuclear, operates a low-level radioactive waste disposal facility, the closest burial ground is approximately 2.2 km from the Craig's Pond area and Chem Nuclear management reports that there have been no direct inputs of contaminants to the system (personal communication to M. Arbogast; Arbogast, 1999). Despite the lack of direct contaminant inputs into the area, previous investigations have revealed elevated levels of ^{137}Cs in raccoons collected from the Craig's Pond/Sarracenia Bay area (Arbogast, 1999), which are likely due to movements to waste sites within the SRS boundary (Boring, 2001).

3. Raccoon model development

3.1. Radio-tracking and home range determination

Thirteen radiocollared male raccoons were located 845 times between March 1999 and August 2000. Male raccoons were used in this long-term study to preclude taking females with young out of the population. Animals were located during the day (0700–1900 h) once per week by approaching daytime resting locations on foot using a portable telemetry receiver (AVM Instrument, Livermore, CA, USA; Telonics, Mesa, AZ, USA) coupled with a flexible two-element yagi antenna (Telonics). Raccoon locations were recorded using a handheld Global Positioning System (Garmin, Olathe, KS, USA). Night locations (1900–0700 h) were estimated using triangulation methods (White and Garrott, 1990), in which a minimum of two (usually three) compass bearings were recorded from surveyed tracking stations established along roads (see Boring, 2001 for more detailed description of tracking). Azimuth data obtained from triangulation was processed using the Lenth (1981) Maximum Likelihood Estimator (as presented by White and Garrott, 1990) to produce point estimates of animal locations. The program CALHOME (Kie et al., 1996) was used to construct 95% overall home ranges using the Adaptive Kernel Method (Worton, 1987). CALHOME utilizes the Epanechnikov kernel (Worton, 1989) and assumes that the data follow a bivariate normal probability distribution when calculating the optimal bandwidth h_{opt} (called a smoothing parameter by Worton, 1989). When animal location data appeared to be non-normally distributed (i.e. animals appeared to be using several core areas), the bandwidth was decreased in 10% increments until the lowest possible least-squares cross-validation (LSCV) score was reached without causing the 95% home range polygons to break up into several polygons (Kie et al., 1996). Per direction of the CALHOME authors, bandwidths were never reduced below 0.8 of the optimal as determined by the program (Kie, personal communication, Kie et al., 1996). Home range estimates were derived only for animals with $\geq$30 radiolocations (Seaman et al., 1999). All 13 raccoons used in this study had $\geq$30 radiolocations. Seasons and daytime/nighttime locations were pooled since no significant seasonal or diurnal habitat utilization differences were found (Boring, 2001).

3.2. Data structure and model development

The best approach for determining the likelihood of a species being in a specific area is through the understanding of key life history components. The success of applying life history components to dynamic ecological models in a GIS is dependent upon the quality of habitat data available. The SRS habitat GIS data layers supply such information with the key component being the 2000 habitat data layer (HABMAP) with 33 habitat classifications (Table 1). Other integral data layers essential to model development were those associated with watershed hydrology—river/streams, reservoirs, as well as Carolina

Table 1
Categories, area, and percent composition of habitats for the 2000 version of the SRS HABMAP (Pinder et al., 1998)

HABID	Habitat category	Hectare (ha)	Percent composition (%)
1	Industrial	525.42	1
2	Water	1822.32	2
3	Bare Soil/Bare Surface	236.97	0
4	Sparse Herbaceous Vegetation	1085.58	1
5	Grasses and Forbs	3076.11	4
6	Shrubs, Grasses and Forbs	2555.46	3
7	Disturbed and Revegetated in 1997	124.29	0
8	Marsh/Macrophyte	416.88	1
9	Open-canopy Pine	29804.04	37
9M	Young, open-canopy loblolly	3631.23	5
9M	Open-canopy loblolly	12053.6	15
9M	Young, open-canopy longleaf	2615.85	3
9M	Open-canopy longleaf	2709.09	3
9M	Open-canopy slash	1587.51	2
9M	Young, open-canopy slash	6882.21	9
9M	Open-canopy pines	324.54	0
11	Dense-canopy Pines	13741.38	17
11M	Young, dense-canopy loblolly	2546.46	3
11M	Dense-canopy loblolly	54	0
11M	Dense-canopy longleaf	4153.77	5
11M	Young, dense-canopy longleaf	64.17	0
11M	Young, dense-canopy slash	2874.69	4
11M	Dense-canopy slash	3702.24	5
11M	Dense-canopy pines	346.05	0
23	Evergreen Hardwoods	845.37	1
24	Upland Hardwoods	6373.98	8
25	Upland Oak Hardwoods	1469.07	2
26	Mixed-composition Floodplain Hardwoods	1323.63	2
27	Floodplain Oak Forests	1323	2
28	Floodplain Sweetgum Forests	7010.73	9
29	Mixed Bottomland Hardwoods	3486.96	4
30	Bottomland Hardwoods and Cypress	308.43	0
31	Baldcypress/Water Tupelo	2595.87	3
32	Upland Scrub Forests	2131.02	3
33	Wetland Scrub Forests	84.78	0

The map was compiled from supervised classifications of Landsat Thematic Mapper Data from February, April and July 1997 with a resultant pixel size of 30 m. Additional detail was supplied by cross-referencing the classifications of spectral data with soil data (Looney et al., 1990) and the U.S. Forest Service management plan for the SRS and habitat categories were updated in 2000. An identification number (HABID) was given to each habitat category and is often referenced as such in the text. An "M" was given as a HABID if that habitat category was merged into the above numeric category before GIS analyses were performed.

bays and other isolated wetlands. These data layers were used to determine the minimum distance to water and the number of wetlands within a core raccoon area.

The detailed HABMAP of the SRS was constructed with the purpose of describing the abundance and distributions of habitats and land uses surrounding the SRS. Habitat information was classified with intentions to assess which animal species may be present at a location for use in ecological risk assessments (Pinder et al., 1998). The map was compiled from supervised classifications of Landsat Thematic Mapper Data collected in February, April and July 1997, to allow proper assessment of habitats, with a pixel size of 30 m. Additional detail was supplied by cross-referencing the classifications of spectral data with soil data (Looney et al., 1990) and the U.S. Forest Service management plan for the SRS. In 2000, this habitat map was updated using timber harvest information provided by the U.S. Forest Service and was ground truthed by various SRS researchers.

For the purposes of providing meaningful habitat categories germane to the life history of the raccoon, certain habitat classes were merged into single categories a priori to any habitat analyses (Table 1). Specifically, the 14 pine categories were merged into either "open-canopy pine" or "dense canopy pine". Other habitat categories were also merged and used in the model as single potential variables if the original habitat category did not enter the model. Specifically, the open wetland habitats (HABID 2 and 8, Table 1) were merged into the variable WATMAR; herbaceous habitats (HABID 4 to 6, Table 1) were merged into the variable GRASS; upland hardwood habitats (HABID 23 to 25, Table 1) were merged into the variable UPHRDWD; and floodplain forest habitats (HABID 26 to 31, Table 1) were merged into the variable FLDPLN. Again, these merged habitat categories were only used as potential variables in the logistic regression if the original habitat categories did not contribute to the model. Therefore, an individual habitat that was used in a merged category was never used in the model if the category into which it was merged was used.

The raccoon model was developed from three sub-models using the habitat usage information derived from the radio-telemetry study for male raccoons.

Therefore, the final model only applies to the distribution of male raccoons on the SRS. An inductive approach (Corsi et al., 2000; Gaines et al., in press) was used to develop the three sub-models using the ecological requirements of raccoons inhabiting the following ecotones: (1) reservoir systems (using data from Pond B raccoons), (2) bottomland hardwood/riverine systems (using data from the Steel Creek raccoons), and (3) isolated wetland systems (using data from Craig's Pond raccoons). Wetland ecotones were chosen for monitoring raccoon populations because this species has a proclivity for water and past studies have indicated that home ranges and movements are centred near waterbodies (Jenkins et al., 1979; Gehrt and Fritzell, 1998). For each of the three sub-models, the 95% home range polygons of all raccoons studied in that area were merged to represent one study location. Raccoons in each of these areas had overlapping home ranges and did not appear to be territorial; therefore, merging the home ranges represented the available habitat for raccoons inhabiting these systems. For the purposes of this study, home range is defined as the "area included in the daily, seasonal and annual travels of an individual animal" (Bolen and Robinson, 2003) as calculated by the methods described above. Since the maximum triangulation error for each radiolocation was an area of 3.24 ha (Boring, 2001), the minimum area that could be used to investigate habitat structure was individual units of that size. This scale represents the immediate habitat structure available at the location an individual was located.

To investigate habitat associations at this scale, a mesh of 3.24-ha hexagons was draped over the data layers used to analyze habitat composition. The hexagonal mesh has the intrinsic advantage that all neighboring cells of a given cell are equidistant from the cell's center point. This is useful in radial searches and retrievals around the cell's centroid. Further, a hexagonal polygon is the least complex shape (lowest edge/area ratio) that most closely approximates a circle that can still be meshed without overlapping or producing gaps. This lower edge effect is desirable for habitat analyses and allows transparent and highly explicable analyses of landscape pattern. It also facilitates multiple scale landscape pattern analyses such as the one performed here (Elkie et al., 1999). The hexagonal mesh allowed those pixels whose centroid fell within the boundary of the hexagon to be analysed. Since the resolution of the HAPMAP was 30 m^2 compared to a much larger 10-ha resolution of the hexagonal mesh, both omission and commission error is minimal. This process was repeated at two larger resolutions, 10 and 15 ha, which was the average size of the 30% and 50% core areas found within the raccoon's home range. Raccoon 95% home ranges ranged from 143.7 to 372.0 hectares (ha) and averaged 216.1 ± 70.0 ha. The core area represents the areas that were used consistently (as represented as a percentage) by the raccoon within its home range. Each resolution was modelled to determine at what scale SRS raccoons were most sensitive to habitat structure and a hexagonal size of 10 ha was deemed most appropriate based on model convergence and maximum rescaled r^2 values (see Gaines et al., in press for further detail). Specifically, none of the 3.24-ha sub-models statistically converged and all 15-ha sub-models had very low maximum rescaled r^2 values as compared to the 10-ha sub-models. Habitat distribution and landscape indices (Appendix A) were determined for each hexagon and used as independent variables to be considered for analysis of habitat selection under the assumption that the habitat associations were largely influenced by habitat composition. The specific variables used were:

(1) Habitat area (for each of the habitats that were available in the merged 95% home range polygon),
(2) Number of wetlands present in a hexagon,
(3) Distance to nearest wetland,
(4) Class Landscape Metrics-Patch Density and Size Metrics, Edge Metrics, Shape Metrics (Appendix A) using FRAGSTATs ver 2.0; see McGarigal and Marks (1995) for further arithmetic narrative.

In these models, the class for the landscape metric represented the scale of the predictive parameters. The size of the hexagon defined the scale at which the species resource use of the SRS was predicted (in this case 10 ha). These class-level indices describe the structure of the landscape for each hexagon and therefore can be used as predictive parameters with the response variable. Logistic regression was used to derive probabilistic resource selection functions using the independent variables described above (Manly et al., 2002; Hosmer and Lemeshow, 2000). The number of times a raccoon utilized a hexagon within the study area was determined (e.g. 0–n) and used as a weighting function for the independent variables within the regression. To minimize collinearity among explanatory variables, a correlation matrix was used to determine what variables provided redundant information. To derive the most parsimonious variable combinations that best discriminated used landscapes, the Akaike information criteria (Akaike, 1974; Manly et al., 2002) was used for contributing variables. Model output was the probability (p) within a hexagon that the variable attribute combination at any given site defines the species habitat (Chou, 1997; Apps et al., 2001; see Tables 2–4 for model parameter output).

3.3. Geographic Information System Application

A final GIS data layer representing the probability of raccoon inhabiting a hexagon was constructed by applying the probabilistic function derived from the

Table 2
Logistic regression summary statistics for the 10-ha RIVER model

Analysis of maximum likelihood estimates					
Variable	*df*	Parameter estimate	Standard error	Chi-square	*P*-value
Intercept	1	2.6935	3.5036	0.5910	0.4420
# of wetlands	1	1.4623	0.9484	2.3771	0.1231
MPE	1	0.1435	0.1174	1.4934	0.2217
MPAR	1	0.0283	0.0199	2.0295	0.1543
WATMAR	1	−10.6217	2.5856	16.8759	<0.0001
Grasses and Forbs	1	−9.1636	4.4515	4.2376	0.0395
Dense-canopy Pines	1	−12.0898	2.5696	22.1366	<0.0001
Evergreen Hardwoods	1	15.7592	4.1773	14.2321	0.0002
Upland Hardwoods	1	−10.1934	2.4213	17.7236	<0.0001
Upland Oak Hardwoods	1	−19.2744	12.0674	2.5511	0.1102
Mixed-composition Flood plain Hardwoods	1	−4.1054	1.6858	5.9308	0.0149
Flood plain oak forests	1	20.7499	13.4171	2.3917	0.1220
Upland Scrub Forests	1	−17.1781	10.4071	2.7245	0.0988

Observations (n=80) are the number of 10-ha hexagons used in the Steel Creek study area. The Akaike information criteria (AIC) (Akaike, 1974; Manly et al., 2002) was used for the model-building process.

Table 3
Logistic regression summary statistics for the 10-ha RESERVOIR model

Analysis of maximum likelihood estimates					
Variable	*df*	Parameter estimate	Standard error	Chi-square	*P*-value
Intercept	1	−196.0	64.7579	9.1582	0.0025
# of wetlands	1	4.9697	1.3483	13.5854	0.0002
Minimum distance to water	1	−0.6525	0.1618	16.2748	<0.0001
MSI	1	−16.3869	7.5050	4.7675	0.0290
MPFD	1	89.9499	28.1622	10.2016	0.0014
AWMPFD	1	85.5610	40.5046	4.4621	0.0347
WATMAR	1	13.0723	3.4804	14.1074	0.0002
Shrubs, Grasses and Forbs	1	12.7037	5.2978	5.7500	0.0165
Upland Hardwoods	1	8.1614	3.3228	6.0328	0.0140
Upland Oak Hardwoods	1	−19.8173	6.5401	9.1816	0.0024
Mixed-composition Flood plain Hardwoods	1	−13.8339	9.3859	2.1724	0.1405
Mixed Bottomland Hardwoods	1	14.4381	5.6103	6.6230	0.0101
Open-canopy Pine	1	18.7779	5.1308	13.3946	0.0003
Dense-canopy Pine	1	9.5450	2.6027	13.4494	0.0002
Upland Scrub Forests	1	−26.7682	8.6775	9.5159	0.0020

Observations (n=67) are the number of 10-ha hexagons used in the Pond B study area. The Akaike information criteria (AIC) (Akaike, 1974; Manly et al., 2002) was used for the model-building process.

Table 4
Logistic regression summary statistics for the 10-ha BAY model

Analysis of maximum likelihood estimates					
Variable	*df*	Parameter estimate	Standard error	Chi-square	*P*-value
Intercept	1	−14.3268	9.8457	2.1174	0.1456
# of wetlands	1	2.5552	1.0587	5.8253	0.0158
NUMP	1	2.1849	1.4738	2.1980	0.1382
MPS	1	6.0283	5.2150	1.3362	0.2477
Minimum distance to water	1	−0.1211	0.0602	4.0450	0.0443
Open-canopy Pine	1	4.0463	2.3382	2.9947	0.0835
Dense-canopy Pine	1	1.7099	1.2681	1.8182	0.1775
Evergreen Hardwoods	1	−16.7700	7.2016	5.4225	0.0199
Mixed Bottomland Hardwoods	1	9.6507	6.3609	2.3019	0.1292

Observations (n=66) are the number of 10-ha hexagons used in the Craig's Pond study area. The Akaike information criteria (AIC) (Akaike, 1974; Manly et al., 2002) was used for the model-building process.

logistic regression to the appropriate hexagon based on the following rules:

(1) The river sub-model was the principal model applied since most of the non-industrial facility areas on the SRS are associated with one of the major river/stream drainages.
(2) The reservoir sub-model was applied to the three adjacent hexagons surrounding any reservoir and was dominant over the river model. That is, even if there was a riverine habitat in any of the three hexagons surrounding a reservoir, the reservoir sub-model was applied. This distance was based on movements derived from the home range analyses.
(3) The bay sub-model was applied to those hexagons that intersected a bay and was dominant over the river and reservoir sub-models. This minimal distance was also derived from movement data associated with the home range analyses and the juxtaposition of bays relative to the river drainages.

3.4. Model validation

A randomization function was employed as the statistical validation procedure to evaluate the strength of the model's prediction (Manly, 1998). The leave-one-out cross-validation procedure was used to produce the predicted binomial observation (0 vs. 1) by dropping the data of one observation from the dependent variables and re-estimating the response from the tested model (Neter et al., 1990). The observation was then put back into the data set and the procedure was repeated until all observations were used. The model's validity was then judged by dividing the number of observations for which there were accurate estimates by the total number of observations in the data set.

A second validation was performed by comparing the model's prediction of raccoon use to a trap-line census from 1977 to 1982 (Jenkins et al., 1979). Ten transects, each approximately 3.2 km long, within the SRS were used to trap raccoons every fall (Fig. 1). Captured animals were marked and released. No recaptures were used in the validation process. Three spatial scales were used to determine how well the model performed compared to the furbearer trap data. A 1500-m buffer of each trap-line representing the average diameter of a raccoon home range, a 750-m buffer representing the average radius of a raccoon home range, and the actual hexagon (390-m 'diameter') of the distribution model that the trap-line overlaid on, were used to investigate the model's predictive strength. The number of individual raccoons that were trapped in each trap-line over the 5-year period was compared to the mean probability of raccoon occurrence for each scale by summarizing usage by four categories: low, medium, high, and very high. Specifically, trap data were separated into four even categories of low (0–4), medium (5–9), high (10–14), and very high (15–18) based on the highest frequency of catches. Distribution probabilities were also broken into the same evenly distributed categories (low (0–0.25), medium (0.26–0.50), high (0.51–0.75), very high (0.76–1.0)). To ensure that habitats did not change significantly between the trapping period and the habitats from the 2000 habitat map, the areas within the 1500-m buffer zone were compared to a habitat map from 1988 using a paired *t*-test. This habitat map had the same habitat categories as the 2000 habitat map within those buffer zones. No significant habitat changes were found (P's>0.95); therefore, a Spearman's rank correlation was used to test how well the trap-line categories and the probabilistic model categories correlated using each transect as a replicate.

4. Body-burden estimates

4.1. Spatially explicit uptake ^{137}Cs estimates for steel creek

^{137}Cs uptake models were constructed from information collected for male raccoons from three consecutive annual trapping efforts in Steel Creek located near the border of the SRS (Fig. 2) that is next to a private hunting ground. This population was used because individuals spent 100% of their time in contaminated areas (as determined from the radio-telemetry study), thereby providing the expected mean upper limit of ^{137}Cs uptake in muscle tissue for individuals living in that contaminated floodplain. Mean ^{137}Cs levels declined significantly from the first

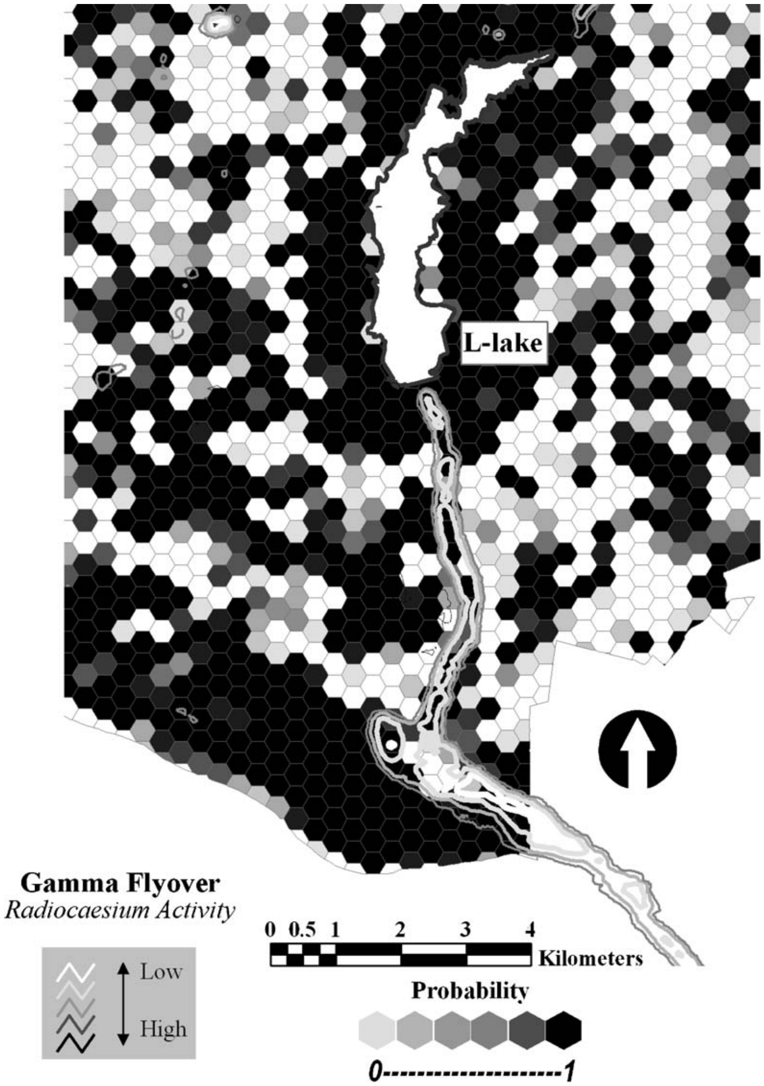

Fig. 2. Map of the Steel Creek region contaminated with radiocaesium (^{137}Cs), as shown by isopleths, downstream from the L-Lake reactor-cooling reservoir. Hexagons (10 ha) represent the raccoon distribution model's prediction probability ($0 \leq P \leq 1$) of raccoon occurrence.

trap effort to the third trap effort (Year 1: 0.127 Bq g^{-1}, Year 2: 0.063 Bq $g^{-1}$and Year 3: 0.029 Bq g^{-1}; all activities are reported for wet weight; see Arbogast, 1999; Boring, 2001 and Gaines et al., 2000 for analytical counting methods). The first two trapping efforts (Arbogast, 1999; Gaines et al., 2000) removed 10 individuals from the population each year (spring 1997 and spring 1998). The third trapping effort (spring 1999; Boring, 2001) were those individuals used in the telemetry study that was used for model development. Areas were trapped until no more individuals were caught after an additional 2-week period. Therefore, it is assumed that the sample size represents the population of male raccoons for the immediate area. For the first trapping effort, muscle was removed from raccoons and analyzed for ^{137}Cs. For the second trap effort, both muscle and whole body ^{137}Cs burdens were determined and a simple linear regression was performed to determine their predictive relationship. For the third trap effort, whole body ^{137}Cs burdens were determined for all captured raccoons (n=14). The muscle concentration was estimated using the simple linear regression model developed from the second trap effort (wet weight muscle concentration [Bq g^{-1}]=1.7041*whole body [Bq g^{-1}]+0.0031; r^2= 0.9617; Arbogast, 1999).

A model to predict the spatial distribution of ^{137}Cs levels in raccoon muscle tissue for the Steel Creek region (Fig. 2) was constructed by multiplying the amount of ^{137}Cs in the raccoon muscle tissue by the probability of an animal being in the contaminated regions of Steel Creek located downstream of the L-lake reactor cooling reservoir. The areas where raccoons were trapped had the highest probabilities of occurrence in the ^{137}Cs-contaminated areas of Steel Creek as can be seen by the gamma over flight data (Fig. 2). The EPA 10^{-6} human cancer risk from consumption for ^{137}Cs was calculated and applied to the model as a data layer that displayed the risk level in relation to the distribution of ^{137}Cs and the species' probability of occurrence in that location. The EPA's guidelines for Superfund sites (USEPA, 1989) was used to estimate the amount of game meat at the average ^{137}Cs level recorded that an individual could consume per year and still maintain the risk from eating the particular game food below the EPA action level of 1×10^{-6} excess lifetime fatal cancers. This estimation was derived using the EPA's Integrated Risk Information System (IRIS; USEPA, 1997). This calculation was based on the equation:

$$\mathrm{EC} = \mathrm{SF} \times M \times \mathrm{IR} \qquad (1)$$

where: EC=Excess Cancer (cases $year^{-1}$); SF=Slope Factor (cases Bq^{-1})=3.16×10^{-11} excess lifetime fatal cancers Bq^{-1} (Eckerman et al., 1999); M=Game Muscle Specific Activity (Bq g^{-1} wet mass); IR=Ingestion Rate (g $year^{-1}$).

An estimated consumption rate of 12, 350-g meals per year was based on interviews with sportsmen who consume raccoon meat in South Carolina (Gaines et al., 2000).

5. Results

The best-fit logistic regression model for the river raccoon distribution sub-model used nine habitat categories, wetland presence and two landscape metrics (Table 2). The parameter estimates of the number of wetlands, evergreen hardwoods, floodplain oak forests and both landscape metrics were positive, indicating that raccoons favoured these habitats. However, raccoons avoided grasses and forbs, water/marsh, both pine categories, upland hardwoods, upland oak hardwoods, and upland scrub forests as indicated by the negative parameter estimate. Based on the rules described in the methods, this model was applied to 81% of the total area of the SRS. Validation procedures showed that this model predicted non-use correctly 62% of the time and predicted use correctly 100% of the time.

The reservoir model also used nine habitat categories with three landscape metrics and two wetland metrics (Table 3) and comprised 10% of the total SRS area. Raccoons favored increased area of upland oak hardwoods, mixed-composition flood plain hardwoods and upland scrub forests. The minimum distance to water and mean shape index (MSI) landscape metric parameter estimates were also positive. The parameter estimates were negative for the number of wetlands, mean patch fractal dimension (MPFD), area-weighted mean patch fractal dimension (AWMPFD), water/marsh, shrubs/grasses and forbs, upland hardwoods, mixed bottomland hardwoods, and both pine categories. This model predicted non-use correctly only 40% of the time, and predicted use correctly 97% of the time.

The bay model used only four habitat categories, two landscape metrics, and two wetland metrics (Table 4) and was applied to 9% of the SRS based on the rule-based system. The parameter estimates of the number of wetlands, both pine categories, mixed bottomland hardwoods, number of patches (NUMP), and mean patch size (MPS) were positive. The parameter estimates for evergreen hardwoods and minimum distance to water were negative. This model performed the poorest in validation procedures with only 17% of non-use predicted correctly. However, it did predict usage correctly 98% of the time. As a whole, the three distribution models combined also tended to over predict usage of areas that had low trapping success based on the 5-year furbearer trapping data (Table 5).

The furbearer trap-line data used as an independent validation, correlated well with the raccoon distribution model's prediction strength at the smallest scale where

Table 5
Predicted raccoon distributions on the Department of Energy's Savannah River Site as compared to furbearer trapping data from 1977 to 1982 along 10–3.2-km trap-lines (Fig. 1)

Trap-line	Total catches (1977–1982)	Total catch category	One hexagon[a]	750-m buffer[b]	1500-m buffer[c]
1	1	Low	Medium	High	High
2	15	High	Very High	High	Medium
3	18	Very High	Medium	Medium	Medium
4	12	Medium	High	High	High
5	4	Low	Medium	High	High
6	15	High	Very High	Very High	Very High
7	1	Low	Medium	High	Medium
8	4	Low	Low	Medium	Medium
9	7	Medium	Medium	Medium	Medium
10	3	Low	Low	Medium	Medium

Trap data are broken into four even categories of low (0–4), medium (5–9), high (10–14), and very high (15–18) based on the highest frequency of catches. Distribution probabilities are also broken into the same evenly distributed categories (0–0.25, 0.26–0.50, 0.51–0.75, 0.76–1.0). A 1500-m buffer of each trap-line representing the average diameter of a raccoon home range, a 750-m buffer representing the average radius of a raccoon home range, and the actual hexagon (390-m 'diameter') of the distribution model that the trap overlaid on, were used to investigate the model's prediction strength.

[a] Spearman rank correlation (r=0.66, P=0.03, df=9).

[b] Spearman rank correlation (r=0.10, P=0.78, df=9).

[c] Spearman rank correlation (r=0.02, P=0.95, df=9).

only the actual hexagon that the trap-line fell on was used (r=0.66, P=0.03, df=9; Table 5). All other scales did not correlate with the trap-line data (P>0.50).

The predicted ^{137}Cs burdens in raccoons inhabiting the entire contaminated Steel Creek system and estimated consumption risk as predicted by utilizing the distribution model, were only 69% of their original estimated values which assumed 100% use by raccoons (Table 6a,b). Specifically, ^{137}Cs burdens were 0.088, 0.043 and 0.020 Bq g^{-1} wet muscle, with the corresponding estimated additional life time cancer risks from consuming raccoons of 3.7×10^{-7}, 2.3×10^{-7}, and 6.4×10^{-7} for harvests 1 through 3, respectively (Table 6b).

6. Discussion

Using a multimodel approach to estimate species occurrence provided the necessary means to develop distribution models that were appropriate to different ecosystems. These sub-models then could be utilized to estimate potential ^{137}Cs burdens to raccoons that reside in contaminated systems, thereby providing a potentially more realistic estimate of human consumption and ecological risk. However, any model is an estimation that relies on the quality of the input data as well as the parameters that are estimated, and therefore has inherent biases and inaccuracies and should be used with appropriate caution. The raccoon distribution model was derived using data only from adult male raccoons and therefore some of its aspects may not be applicable to some other age/sex cohorts. However, this model

Table 6
(a,b) ^{137}Cs Raccoon Muscle Tissue (Bq g^{-1}) least square (LS) mean, upper and lower confidence intervals (CI), and excess lifetime cancer risks (1×10^{-6}) predicted to have resulted from consumption of raccoon meat for the Steel Creek region of the Department of Energy's Savannah River Site (SRS)

Harvest	^{137}Cs Raccoon muscle tissue (Bq g^{-1})			Excess cancer risk		
	LS Mean	Lower (95% CI)	Upper (95% CI)	LS Mean	Lower (95% CI)	Upper (95% CI)
(a)						
1	0.127	0.073	0.22	5.39×10^{-7}	3.10×10^{-7}	9.34×10^{-7}
2	0.063	0.036	0.109	2.68×10^{-7}	1.53×10^{-7}	4.63×10^{-7}
3	0.029	0.018	0.047	1.23×10^{-7}	7.64×10^{-8}	2.00×10^{-7}
(b)						
1	0.088	0.050	0.152	3.71×10^{-7}	2.13×10^{-7}	6.43×10^{-7}
2	0.043	0.025	0.075	1.84×10^{-7}	1.05×10^{-7}	3.19×10^{-7}
3	0.020	0.012	0.0324	8.48e−08	5.26×10^{-8}	1.37×10^{-7}

(a) shows the values under the assumption that raccoons utilize the region uniformly and (b) shows values based on the raccoon distribution model.

should be generally appropriate for adult female raccoons since, during the radio-telemetry study used to derive this model, it was determined that female raccoons use similar habitats to male raccoons (Boring, 2001). The logistic regression parameters for each sub-model showed that raccoons favored the predominant wetland habitats found in each of the ecotones. The river and bay sub-models indicated that raccoons tended to stay closer to a variety of wetland habitats, possibly exploiting them for a variety of food resources, while the reservoir model showed the opposite. In that case, raccoons tended to consistently stay near the main reservoir water body and did not utilize other water bodies that were found in their home range. This may possibly be explained by the fact that the reservoir itself provides ample food resources as well as large tree stands that can be exploited for denning. The landscape metrics for the river and reservoir sub-models indicated that raccoons favoured larger patches with high shape complexity and avoided small complex patches. Again, this may have to do with resource availability. For the isolated wetland sub-model, patch complexity did not influence raccoon habitat choice, possibly because pine is the dominant habitat surrounding most of the isolated wetlands found on site and these stands have little patch diversity.

The validation procedures indicated that all three sub-models were weakest in predicting non-use, but did perform very well predicting use. This omission error may be due to three major factors. First, the data available/used in the modelling effort did not adequately represent the areas raccoons avoided. This is one possible source of error; however, if this were the case a higher omission error would have been expected for used habitats as well. Secondly, raccoons may have been using what was defined as unused resources and the sampling effort did not capture that use. All areas monitored for the modeling effort were trapped for over 3 years and every effort was made to monitor the entire population. Lastly, the bias associated with the categorisation of used and unused habitats for the logistic regression could have contributed to this error. This most likely contributes the most error, since unused habitats were classified as areas that raccoons were never encountered. An alternative classification could have been low use versus high use. This classification scheme was not employed because it was difficult to determine what “low use” would be in a biological sense. More importantly, this model was derived for the purposes of use in a risk assessment that estimates ^{137}Cs uptake and transport, and was constructed to err on the side of over prediction in order for these estimates to be conservative. Conversely, it could be problematic to utilise the model to determine if raccoons were the appropriate receptor organism for a particular study site. However, this difficulty could be avoided by using raccoons as receptor species in the areas with the highest probabilities. Therefore, when utilising the final predictive model for the SRS, users should be aware that over prediction of raccoon use could occur. However, the strongest model for both use and non-use was the river model that is applied to the largest portion of the SRS, followed by the reservoir and bay models.

The raccoon trap data also support the cross-validation findings, with the smaller scale (one hexagon) validation having the same or higher category as the raccoon trap category, except for transect 3 which was predicted to be used less as compared with other trap-lines. Moreover, as the scale (trap-line buffer) of this validation increased the model’s prediction strength decreased with miscategorisation having no apparent pattern. Since the distribution modelling effort indicated that 10 ha is the most appropriate scale to look at raccoon habitat preference, it is also likely that this is the appropriate scale to look at for trap-line validation.

The final probabilistic distribution model can facilitate both human and ecological risk assessments. Researchers have used these methods to model management scenarios for ecosystem restoration (see DeAngelis et al., 1998), however, relatively few studies have implemented these techniques to aid in the ecological risk assessment process especially in predicting contaminant exposure, uptake and consumption risk. Although humans are often not considered a logical endpoint in an ecological risk assessment, in many cases arguably, they are the most appropriate. When considering the landscape structure of industrial sites such as the SRS (especially those that allow hunting) that are surrounded by rural areas, hunters are one of the main components influencing the population of many wildlife species and subsequently the structure of the ecosystem's foodweb. If hunters were not able to take game from these sites due to high consumption risks, it could have an impact on the population structure of the wildlife in those ecosystems and possibly contribute to new risks due to redistribution and movement of contaminants. For example, the raccoon model shows that there is a high probability of use in the area where the ^{137}Cs risk model was performed (Fig. 2), which is located on the border of the SRS. This habitat structure continues off the SRS, thus providing a potential corridor for contaminated raccoons to move to hunting grounds that border the site.

Predicting ^{137}Cs burdens in raccoon muscle has been presented in a simple form, although the relationship between ^{137}Cs bioavailability and physiological uptake is not. The physical half-life of ^{137}Cs is approximately 30 years. The biological turnover rates within a given organism are influenced by metabolism, and therefore should change based on biotic and abiotic parameters such as age, overall health, seasonality and food availability. Biological turnover rate is also dependent upon the sources and bioavailability of the contaminants within the animal's home range. The distribution model presented here can help estimate and minimize at least some of this variability by predicting the probability of an animal inhabiting that area as a function of proportional use. However, the bioavailability of contaminants is much more complex. When radioactive isotopes are released into an ecosystem such as Steel Creek, the isotopes will theoretically also have an ecological half-life. This is the amount of time required for the level of an isotope (in this case, ^{137}Cs), once established and at equilibrium within a given ecosystem compartment, to decrease by 50%. This is a result of the isotope either becoming ecologically unavailable or being physically removed from a system (Brisbin, 1991). The concept of ecological half-life is further constrained by the fact that most ecosystem compartments are extremely dynamic and rarely come to equilibrium. As the time required to achieve effective equilibrium increases, it becomes less likely that these conditions will remain constant (Peters and Brisbin, 1996). Remobilisation of contaminants can easily occur from wildlife redistributing contaminants through digging and rooting behaviours as well as from abiotic events such as drought and flooding which may influence microbial action. It is extremely difficult to model such a process for an organism such as the raccoon that will move extended distances and utilize many different compartments of an ecosystem. However, the model presented here, along with new understandings of how to quantify resource use (Gaines et al., 2002), can provide a means to better predict exposure and uptake risk in these contaminated environments. Future refinements of this modelling effort should focus on the assimilation and depuration rates of this contaminant in raccoons and how the effects of differential use of contaminated habitats influence this process.

7. Human and ecological risk

The ^{137}Cs dynamics of the SRS is a typical example of how a coupled human-natural system drives ecological risk. Ecosystem dynamics control the ecological half-life of ^{137}Cs, while hunting in and around the SRS influences receptor species population dynamics and thus the bioavailability of ^{137}Cs to humans, other consumers, as well as contaminant transport. Three years of data were used to determine the body burden of raccoons over time harvested in the Steel Creek region and to estimate the associated additional lifetime cancer risk. Raccoon body burden did decrease over the 3-year period most probably because contaminant burdens of the new raccoons, which moved in to reside in that system after removal, had not yet achieved equilibrium. Although physiologically raccoons could reach equilibrium within 6 months (Boring, 2001; Gaines et al., 2000), due to the dynamics of such a productive ecosystem, ^{137}Cs is not consistently bioavailable through each trophic compartment. That is, its ecological half-life is dynamic within the entire Steel Creek system. Utilising the raccoon distribution model to estimate exposure yielded estimates 31% lower than assuming utilization of the Steel Creek contaminated area was constant. This information is extremely important in understanding how contaminants flow into upper trophic levels within an ecosystem, and subsequently determine how system is impacted or "at risk". Further, using the distribution model, the number of meals of raccoon meat that could be consumed at 350 g/meal would be 32, 65 and 141 per year, respectively, based on the 3 years of harvest data without exceeding the U.S. Food and Drug Administration and U.S. Environmental Protection Agency's most conservative action level of a 1×10^{-6} excess lifetime cancer risk (Rodricks, 1992). Considerably, less raccoon meat (22, 44 and 97 meals per year, respectively) could be consumed if 100% use of all habitats were assumed. However, raccoon hunting is not allowed on the SRS property near Steel Creek. Raccoons are hunted on the Steel Creek SRS border, an area for which the model predicts high raccoon use (probabilities >0.90). Therefore, more conservative recommendations such as those that assume 100% use, should be implemented for that region. Moreover, since raccoons from the Steel Creek region are no longer being harvested, the year 1 harvest data would be the most appropriate for risk assessment calculations in the future. Finally, these data suggest that continuous hunting or trap-and-removal in these areas could substantially lower the risk to human consumers as well as contaminant transport (and thus ecological risk) after the first few years of hunting.

8. Conclusions

In this study, raccoons were used as a focal receptor species to investigate how ^{137}Cs moves into the food chain by taking a landscape approach that incorporates the potential movements of this species in its environment. The linear uptake model used to predict ^{137}Cs burdens was a conservative estimate based on a long-term understanding of the dynamics of the contaminated system as well as through monitoring raccoon populations. This approach can also be used to improve estimates of doses not only to humans but also to wildlife for research focused on the protection of the environment from potential toxicants. Besides uptake models, exposure models can also be constructed using these same techniques (see Gaines et al., in press). To be successful, however, models need to be developed using data applicable to that facility. That is, the raccoon distribution model should only be used for other facilities that are in close proximity and share the same ecotypes of the SRS. Constructing such predictive models for wildlife species provides a stand-alone tool consisting of algorithms that are applied within a GIS and therefore dynamic enough to respond to stochastic events such as natural and anthropogenic habitat disturbances and/or long-term changes such as natural succession which is essential to understand how system dynamics affect wildlife populations. This modelling effort serves as a template for DOE managed lands and other large government facilities to establish a framework for site-specific ecological impact assessments that use wildlife species as endpoints. Specifically, predictive distribution models such as this one can: (1) assist in estimating wildlife toxicant exposure and uptake, (2) identify possible contaminant vectors, (3) construct human-based risk assessments from consuming wild game, and (4) examine trophic transfer at multiple scales. However, these models can only estimate the probability that an animal will utilize a habitat and do not predict what it may use that habitat for (e.g. feeding vs. sleeping). In this study, we used the raccoon as a receptor species because it is a habitat generalist and an opportunistic omnivore. Therefore, the assumption that the animal foraged in areas that it inhabited the most is probably valid, which lends to this species being an ideal receptor species for contaminant modelling.

Acknowledgements

This project was funded through the Financial Assistance Award DE-FC09-96SR18546 from the U.S. Department of Energy to the University of Georgia Research Foundation. This research was also partially funded by the Consortium for Risk Evaluation with Stakeholder Participation (CRESP) through the Department of Energy (AI # DE-FC01-95EW55084, DE-FG 26-00NT 40938). We would like to thank Drs. T.G. Chandler, H.N. McKellar, J.M. Novak, M.E. Hodgson, A.B. MacKenzie and two anonymous reviewers for reviewing earlier versions of this manuscript.

Appendix A

Metric definitions of class landscape fractals calculated in FRAGSTATs ver 2.0 (McGarigal and

Marks, 1995) that were used as potential explanatory variables in each logistic regression.

Acronym	Metric (units)	Definition
CA	Class Area (ha)	Sum of areas of all patches belonging to a given class
TLA	Landscape Area (ha)	Sum of areas of all patches in the landscape.
NumP	Number of Patches (#)	Number of Patches for each individual class (e.g. hexagon)
MPS	Mean Patch Size (ha)	Average patch size
MedPS	Median Patch Size (ha)	The middle patch size, or 50th percentile.
PSSD	Patch Size Standard Deviation (ha)	Standard Deviation of patch areas.
PSCoV	Patch Size Coefficient of Variance (%)	Coefficient of variation of patches=PSSD/MPS*100.
TE	Total Edge (m)	Perimeter of patches.
ED	Edge Density (m/ha)	Amount of edge relative to the landscape area. ED=TE/TLA
MPE	Mean Patch Edge (m)	Average amount of edge per patch. MPE=TE/NumP
MPAR	Mean PerimeterArea Ratio (unitless)	Shape Complexity=Sum of each patches perimeter/area ratio divided by number of patches.
MSI	Mean Shape Index (unitless)	Shape Complexity. MSI is greater than one, MSI=1 when all patches are circular (polygons). MSI=sum of each patches perimeter divided by the square root of patch area (ha) for each class (hexagon), and adjusted for circular standard (polygons), divided by the number of patches.
MPFD	Mean Patch Fractal Dimension (unitless)	Mean patch fractal dimension is another measure of shape complexity. Mean fractal dimension approaches one for shapes with simple perimeters and approaches two when shapes are more complex.
AWMPFD	Area Weighted Mean Patch Fractal Dimension (unitless)	Shape Complexity adjusted for shape size. Area weighted mean patch fractal dimension is the same as mean patch fractal dimension with the addition of individual patch area weighting applied to each patch. Because larger patches tend to be more complex than smaller patches, this has the effect of determining patch complexity independent of its size. The unit of measure is the same as mean patch fractal dimension.

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