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Habitat and exposure modelling for ecological risk assessment: A case study for the raccoon on the Savannah River Site

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Abstract

Contamination has a dramatic impact on the health of ecosystem and habitat suitability for the inhabited flora and fauna. The Environmental Protection Agency (EPA) mandates an ecological risk assessment (ERA) that evaluates the potential adverse impact of any anthropogenic activities on the ecosystem (US Environmental Protection Agency, 1997. Ecological Risk Assessment Guidance for Superfund: Process for Designing and Conducting Ecological Risk Assessment. EPA/630/R-021011, Washington, DC). This study provides a general framework and specific procedures to predict the contaminant exposure of mid-sized mammals using a geographical information system (GIS)-based Monte Carlo simulation model. The model was applied to the raccoons (*Procyon lotor*) on the Savannah River Site (SRS), a former nuclear production and current research facility. Habitat behavioral data of 13 radiocollared male raccoons were used to determine home range and core areas. Combined with other geographic data layers, such as distance to water, number of wetlands, and class landscape metrics, a logistic regression model was used to inductively derive the resource selection functions that define the occurrence of raccoon. The cross validation consistently revealed a high accuracy. A Monte Carlo simulation was then performed to estimate the likelihood of exposure and contaminant uptake of the species weighted by the resource selection probability. This model adopted conservative assumptions and spatial parameters. The proposed model served the purpose of assessing ecological risk and supporting decision-making. Implementation issues for a GIS-based ecological risk assessment model are discussed.
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Keywords: Ecologic risk assessment; Geographic information system; Habitat; Exposure; Raccoon; Monte Carlo simulation

1. Introduction

Humans often modify landscapes and can have a dramatic impact on resident flora and fauna, and subsequently, ecosystem health. Basic research has focused on developing ecologically sound models that can be

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used in ecological assessments and has concentrated its efforts to assess the magnitude and probability of a specified undesirable outcome.

There are many types of ecological assessments; each has differed in terms of goals, disciplines and audiences (Suter, 1993). In the United States, the Environmental Protection Agency (EPA) provides the regulatory framework for ecological risk assessments (ERA) to evaluate the potential adverse impact of human activities on the ecosystem (USEPA, 1997). An ERA conducted on large federal government facilities, such as the Department of Energy's (DOE) Savannah River Site (SRS), must comply with the specifications outlined by the EPA (USEPA, 1997). The emphasis of ERA activities on SRS has been largely focused on the movement of radionuclides and other contaminants, and their effects on biotic and abiotic patterns and processes. Previous ERA efforts have been focused on spatially invariant approaches in the form of physical, statistical, or mechanistic models (Suter, 1993). Following the example of many researchers (Haines-Young et al., 1993; Sample, 1994; Frohn, 1997; Hunsaker et al., 2001), DOE started incorporating the techniques of geographic information science, including remote sensing, geographic information systems (GISs) and the global positioning system (GPS) into the process of environmental assessment. However, like any other emerging scientific discipline, there has been a technological and educational gap in adopting GIS to its fullest potential in the application of ERA. Gaines et al. (2005) argue that common practices of "contaminant exposure assessments [for the SRS] took neither the spatial distribution of the pollutant nor the movements of the individual species within the landscape into account". As a result, a critical need has arisen for adopting spatially explicit modelling approaches for ERA to handle the dynamics imposed by heterogeneous environments (Sample and Suter, 1994).

This article presents a GIS-based approach for modelling habitat and ecological risk assessment by environmental managers. The purposes of this paper are (1) to provide a general framework and specific procedures for a contaminant exposure simulation model in wildlife species used as ecological endpoints in ERA, and (2) to discuss problems and limitations in the implementation of GIS-based ecological risk assessment models.

2. Background

In order to understand the fate and transport of contaminants in the ecosystem, it is important to consider wildlife as vectors of contamination in the food chains of 0human and other predators. In fact, using receptor species for targeted contaminant movement is ideal for ERA because different species tend to be appropriate for different spatial scales and may also be ecosystem specific. The SRS currently uses 70 resident wildlife species as focal receptors for the spatially explicit ERA modelling program that we describe in this paper (Gaines et al., 2004). For illustration purposes, a model for the raccoon (*Procyon lotor*) is demonstrated for habitat and exposure modelling in this ERA process.

2.1. Habitat modelling

Considerable research has been conducted on modelling habitat suitability for avian (Brotons et al., 2004; Hirzel and Arlettaz, 2003; Mackay et al., 2002; Manel et al., 1999) and mammalian species (Jerina et al., 2003; Mace et al., 1999; Mlandenoff et al., 1995; Fabricius and Mentis, 1992). Guisan and Zimmermann (2000) provided an excellent review on various steps of predictive habitat modelling and considerations. In general, each model requires as input factors, land cover areas as well as metrics that describe habitat size/shape (Store and Jokimaki, 2003). Spatial characteristics (e.g., proximity, size, heterogeneity, etc.) of habitat type are measured and evaluated for the unique species demands. Habitat suitability (or resource selection function) is then modelled using one of many functions for combining the factors. Weighted linear combination (e.g., analytic hierarchic process, multi-attribute utility theory), generalized linear models (e.g., logistic regression), rule-based or artificial neural networks (ANNs) for combining factors have also been used. Most studies use deductive factor weights defined by experts (Store and Jokimaki, 2003) or limited observation of the species, while some studies have weighted the factors empirically based on observed species use of the habitats (Gaines et al., 2004). Manly et al. (2002) provided comprehensive guidelines in designing ecological studies for various habitat modelling applications.

Recently, many researchers have adopted GIS for predicting habitat suitability for various species. Radeloff et al. (1999) used four habitat parameters as weighted linear function in a GIS to predict population of German roe deer (*Capreolus capreolus*) for wildlife management. Gerrald et al. (2001) employed simple spatial operations such as map overlaying, spatial filters, and buffering to develop a habitat suitability model for the San Joaquan kit fox (*Vulpes macrotis mutica*) in California for planning purposes. Glenz et al. (2001) modelled wolf (*Canis lupes*) habitat suitability by correlating the habitat variables with logistic regression. Debeljak et al. (2001) exploited the landscape and ecological properties by GIS and utilized an expert system of C5 to develop classification trees to assign habitat suitability value for red deer in Slovenia. Kobler and Adamic (2000) adopted a similar inductive approach to identify brown bear (*Ursus arctos*) habitat by automating a learning machine from GIS thematic layers. However, this research differs from previous literature that it concerns the fate and transport of contaminants for ecological risk assessment.

2.2. Exposure modelling

Several years ago, Pastorok et al. (1996a) documented the trends modelling wildlife exposure to toxic materials. The authors criticized recent research in that most assumed no spatial variation in habitat use, no spatial or temporal variation in contaminant sources, and that 100% of the contaminants were available to the wildlife. Although research into one or more of these problems has been conducted, few efforts have attempted to address these spatially and temporally varying habitats and contaminants. In particular, Pastorok et al. (1996b) and Johnson (2002) argue that landscape ecology concepts combined with spatial exposure modelling approaches could be used to capture the spatial variability in habitat use. Monte Carlo simulations have been applied to the uncertainty in contaminant ingestion and body-burden parameter values (e.g., Torres and Johnson, 2001). One of the few spatially explicit exposure modelling approaches that include spatial variation in habitat use and contaminant sources was conducted by Henriques and Dixon (1996). In this study, a GIS and Gaussian plume model were combined with radio telemetry data to model exposure estimates.

2.3. Raccoon habitat

The raccoon is commonly found throughout North America, with high population levels and extended range in a variety of habitats. In non-urbanized settings, it usually inhabits wetlands, plains, and forest with nearby water sources. However, it is extremely adaptable and will utilize human-altered habitats as well. Raccoons are considered potential agents of contaminant movement and dispersal due to their broadly omnivorous diet that includes components of both terrestrial and aquatic food chains (Lotze and Anderson, 1979; Khan et al., 1995). Their high mobility and generalist adaptability allow them to potentially move in and out of contaminated waste sites freely (Gaines et al., 2002). This species is also a game animal that is often hunted and consumed in areas close to the SRS. Previous work has shown that SRS raccoons utilize nearby hunting grounds off the SRS thereby potentially serving as vectors of contaminant transport to offsite habitats and to human consumers (Boring, 2001). For these reasons, the raccoon is a useful receptor species for both human and ecological risk assessments.

There have been difficulties, however, in using raccoons as indicator species for ERA. This is because the raccoon is an opportunistic omnivore, which makes it difficult to estimate its integrated trophic level within the food web. The diversity of its habitat severely complicates the contaminant uptake pattern and its interpretation. Fortunately, recent studies have quantified the contaminant burden of raccoon on the SRS and correlated their relative trophic position using stable isotopic analyses (Gaines et al., 2002). With this new understanding of the relationship between contaminant burden and trophic position, raccoons are ideal receptor species for ERA. Thus, the raccoon was chosen as an appropriate species in a demonstration of a predictive simulation model integrating habitat and contamination uptake parameters for estimating exposure to a population.

2.4. Study area

The SRS is a $778\,km^2$ former nuclear production and current research facility located in west-central South Carolina (Fig. 1) that has restricted public access since 1952. Five nuclear production reactors were installed, produced plutonium, tritium and other nuclear
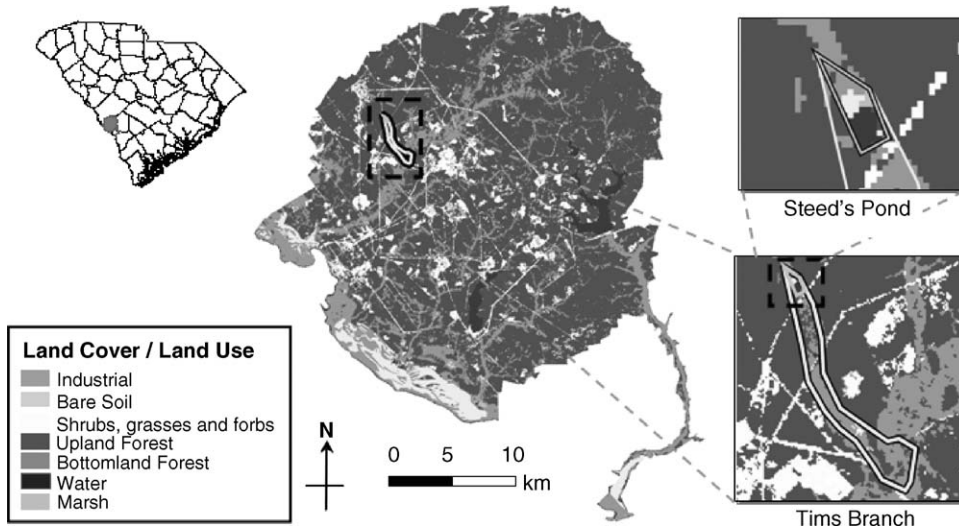
Fig. 1. Location of the SRS and primary land cover types derived from Landsat TM imagery. Inset maps illustrate the waste sites used in this research.

material for national defense and other industrial purposes. The SRS halted nuclear production in 1964. In 1972 it was designated as the first US National Environmental Research Park in the hope of studying the ecological impacts from human activities on the environment and public health (White and Gaines, 2000). Numerous studies on the contamination of the ecosystem and bioaccumulation of radionuclides and metals to the food web have been conducted (Brisbin et al., 1974; Ashley and Zeigler, 1980; Gladden et al., 1985; Whicker et al., 1990).

A large proportion of the SRS is forested, with a mixture of evergreen and hardwood trees in various stages of growth (White and Gaines, 2000). Most areas of the SRS are in close proximity to a water body – including creeks, rivers, wetland depressions, bays, and nuclear reactor cooling reservoirs (although no longer in use for cooling reactor water). The largest contiguous wetlands are associated with the Savannah River Swamp in the southern portion of the SRS.

A major SRS drainage tributary that has been disturbed via large contaminant inputs is the Tims Branch-Steeds Pond depositional system located in the northwest of the SRS (Fig. 1). The simulation model for the raccoon was applied to this system to determine potential contaminant exposure. The boundaries of these waste units are delineated by the DOE based on gamma spectroscopy and mass spectroscopy of soil

and sediment samples. Although the heterogeneity of the contamination is currently being mapped (Gaines and Punshon, unpublished data), the spatial extent of the contamination had to be considered homogeneous for the purpose of this model since these data are not yet available. Steed's Pond was historically a farm pond prior to the establishment of the SRS and served as a de facto settling basin for contaminated sediments produced by upstream processing facilities from the mid-1950s until 1985 (Evans et al., 1992). This pond was reduced from 5.7 to 4.5 ha after partial failure and repair of its dam in the 1960s. Contaminants accumulated within the pond were predominantly U, Ni and Al – which were subsequently left exposed in the wetland environment. Vegetation quickly colonized the area, stabilizing much of it from erosion, with the exception of several unvegetated areas.

It is estimated that approximately 44,000 kg of depleted U were released into Steed's Pond (Pickett, 1990). Ninety-seven percent of the gross α-activity released by the SRS was to the Steed's Pond-Tims Branch stream system, with 61% of this activity being released between 1966 and 1968 (Evans et al., 1992). Until 1979, effluent discharge went to a drainage ditch that flowed into Tims Branch and then into Steed's Pond. Due to a breach of the wooden spillway in 1984, Steed's Pond released sediment-bound contaminants into the Tims Branch depositional environment which

continues during episodic storm events (Batson et al., 1996). Previous investigations have shown that U is bioavailable to wildlife residing in the Steed's Pond region (Punshon et al., 2003a,b). We demonstrate this model, using U as the focal contaminant, using Steed's Pond as a distinct waste site and the Tims Branch depositional area as a second distinct waste site.

3. Methodology

A conceptual model was developed to describe the steps for habitat and exposure modelling undertaken in this research (Fig. 2). First, a receptor species (i.e., the raccoon) was chosen from the list of receptor species at the SRS appropriate for modelling exposure in the focal waste units. This species was chosen based on the knowledge that it uses this site for foraging and thus would potentially be exposed to toxicants. Next, the desired data layers were developed and compiled into a GIS database by using existing data layers, remote sensing, and/or field data collection. A probabilistic resource selection model (i.e., habitat use map) was developed to map the spatial distribution of estimated occupation probabilities. Model validation was performed to evaluate the predictive ability and accuracy of the habitat distribution portion of the model. By using the framework of a generalized exposure model (Sample and Suter, 1994), the level of contaminant burden of individuals occupying different areas in a contaminated area was predicted. A Monte Carlo simulation was used to estimate contaminant exposure for the raccoon population using the Steed's Pond waste site and Tims Branch depositional waste site.

The procedures developed in this study closely follow the specifications suggested by the USEPA (1997). This article presents an illustration of a typical receptor species simulation model for ERA using the raccoon as the endpoint species. The proposed general framework, however, is intended to serve as a template, which can be easily adapted to other receptor species with appropriate modifications of model parameters.

3.1. Raccoon home range

For 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). Dur-
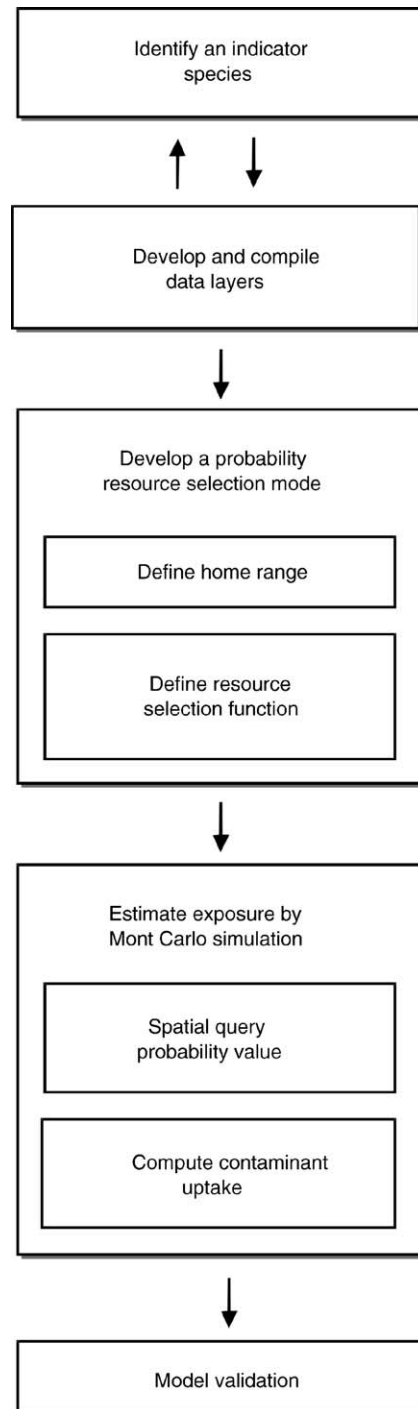

Fig. 2. Conceptual model of the proposed ERA framework.

ing the period of March 1999 and August 2000, 13 male raccoons were radiocollared and located 845 times. Only male raccoons were used in order to preclude the complication of removing females with young from the studied population, which would have had an adverse effect on the spatial movements and population structure of this raccoon population. From previous studies (Boring, 2001), it was determined that adult female raccoons have a similar pattern of habitat selection to male raccoons. The daytime resting areas of the radiocollared raccoons were tracked once every week by a portable telemetry receiver, and recorded by using a handheld GPS unit. Nighttime locations were obtained from triangulation of azimuth data from tracking stations (Boring, 2001). The maximum triangulation error of the telemetry data of raccoon used in this research was 3.24 ha (Boring, 2001). All points were obtained at a minimum of 4 h apart to achieve independence (Swihart and Slade, 1997). Moreover, individual raccoons were not relocated within a 12 h period. No significant diurnal or seasonal variation in habitat utilization was found. Raccoon location data were then pooled across days and seasons. By using the Maximum Likelihood Estimator (Lenth, 1981), point estimates of the raccoon locations were created (White and Garrott, 1990). The 95% home range ellipses were computed by using the Adaptive Kernal Method of the program CALHOME (Worton, 1987; Kei et al., 1996). The final home range estimates were based only on animals that have ≥ 30 radiolocations (Seaman et al., 1999).

3.2. Probability resource selection model

For a better estimation of the likelihood of a species foraging in a particular area, it is important to consider habitat composition and their spatial characteristics. The resource selection model was developed using a habitat map (Fig. 1) derived from supervised classification of Landsat Thematic Mapper imageries (30 m resolution) collected in February, April and July 1997 (Pinder et al., 1998; Gaines et al., 2004). The habitat map was later improved by using soils data (Looney et al., 1990) and the US Forest Service management plan for the SRS. The raccoon model was developed from habitat usage information derived from the radio-telemetry study for male raccoons (see Gaines et al., 2005 for detailed methodology) using an in-

ductive approach (Corsi et al., 2000; Gaines et al., 2004). The 95% home range polygon was merged to represent one study location. Raccoons had overlapping home ranges and did not appear to be territorial; therefore merging the home ranges represented the available habitat for raccoons (Boring, 2001; Gaines et al., 2005). To determine the appropriate scale at which to investigate resource selection, we used the maximum triangulation error for each radiolocation (3.24 ha; Boring, 2001; Gaines et al., 2005), as the minimum unit that could be used to investigate habitat structure. 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.

To investigate habitat associations, a hexagonal mesh was draped over the data layers used to analyze habitat composition for each scale. The hexagonal mesh allowed those pixels whose centroid fell within the boundary of the hexagon to be analysed. Since the resolution of the habitat map was 30 m × 30 m compared to a much larger 10 ha × 10 ha resolution of the hexagonal mesh, both omission and commission error is minimal. Specifically, logistic regression was used to derive probabilistic resource selection functions using habitat characteristics and landscape indices as independent variables (Manly et al., 2002; Hosmer and Lemeshow, 2000; see Gaines et al., 2005 for detailed methodology). These variables included: (1) habitat area, (2) number of wetlands within the core area, (3) distance to water, and (4) class landscape metrics (McGairal and Marks, 1993). Raccoon presence or absence in a hexagon was used as the dichotomous response variable. 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. 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 convergance and maximum rescaled R^2 values (see Gaines et

Table 1
Logistic parameters and estimates for the raccoon distribution model

Variable	Parameter estimate
Intercept	2.6935
Presence of wetland	1.4623
Mean patch edge (meters)	0.1435
Mean perimeter-to-area ratio	0.0283
Water/marsh (WATMAR)	−10.6217
Grasses and forbs	−9.1636
Dense-canopy pines	−12.0898
Evergreen hardwoods	15.7592
Upland hardwoods	−10.1934
Upland oak hardwoods	−19.2744
Mixed-composition floodplain hardwoods	−4.1054
Floodplain oak forests	20.7499
Upland scrub forests	−17.1781

al., 2005, for further detail). The raccoon model used here was based on 13 independent variables (Table 1). The result of the model was a probability map indicating the likelihood of raccoon use across the SRS (Fig. 3).

3.3. Monte Carlo simulation for exposure estimates

Estimating the exposure of raccoons to a hazardous material requires an empirical relationship between the probability of foraging at a location and the risk of contamination exposure from using resources at that location. The probability resource selection model provides the functional basis for the ERA. This model was implemented using knowledge of the spatial distributions of contaminants, an animal's home range, and spatial extent of the waste site.

The exposure to a raccoon at a location is computed as a function of body weight, ingestion rate of media, and the concentration of contaminants within the media. The total exposure to raccoons foraging at a waste site was modelled as a function of the ratio of waste site area to home range area weighted by the probability of the animal occurring within the area defined by its hypothetical home range:

$$E_j = P \left(\frac{\text{WSA}}{\text{HR}} \left[\sum_{i=1}^{m} \left(\frac{\text{IR}_i C_{ij}}{\text{BW}} \right) \right] \right) \tag{1}$$

where E_j is the total exposure to contaminant j in mg/kg/d, P is the average probability of the species inhabiting a waste site, WSA is the waste site area within the home range in ha, HR is the home range area in ha, m is the total number of ingested media (e.g., food, water, soil), IR_i is the ingestion rate for media I, C_{ij} is the concentration of contaminant j in medium i in
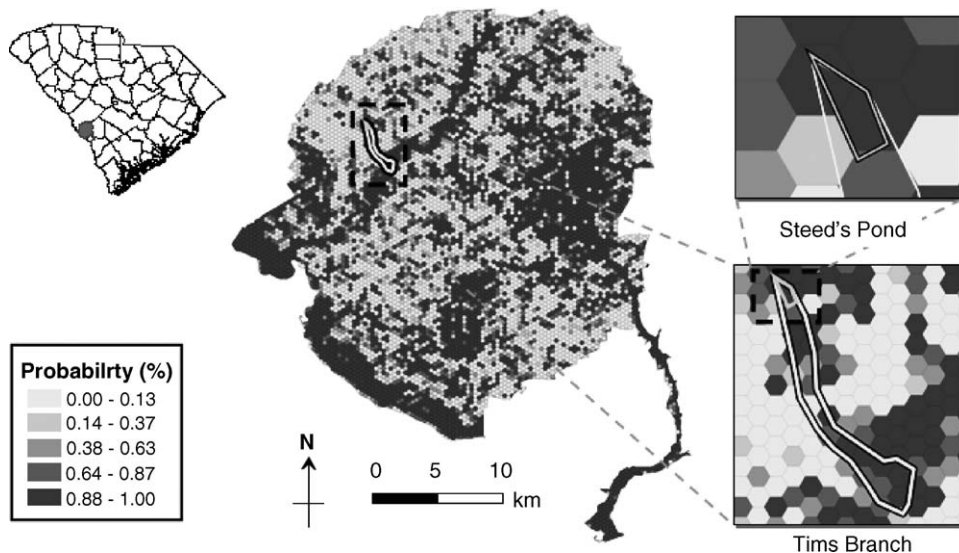

Fig. 3. Probability of a raccoon using locations in the SRS. The hexagonal tessellation uses a unit size of 10 ha, equivalent to the average core area of a raccoon. Inset maps illustrate the waste sites used in this research.

mg/kg; BW is the whole body weight of the endpoint species in kg.

The contaminant exposure modelled by Eq. (1) is a modified exposure estimation based on the work of Sample and Suter (1994), in which the proportion of the contaminated area that is suitable for the animal's use is replaced with the probability derived from the resource selection model. This offers improved rigor for estimating exposure because it eliminates the ambiguity inherent in defining suitability. To get a distribution of the total exposure of a single raccoon as well as a potential population foraging near the waste site can be derived using a Monte Carlo simulation of the probability of raccoon use within the waste site area.

Monte Carlo simulation uses random number generators to simulate a variety of statistical and experimental conditions, often based on sample observations (Gentle and James, 1998; Murdoch, 2000). Here, we sampled hypothetical home ranges spatially by randomly assigning a centroid within a specified area around the waste site, based on the uniform distribution. This procedure mimics sampling from the population of possible home ranges. This example uses spatial units (hexagons) smaller than the animal's home range. Therefore, during the simulation process, hypothetical home range ellipses must be used. We then calculate exposure for each sampled hypothetical home range based on the joint occurrence of model values (e.g., habitat use) and the model estimated probabilities of finding a raccoon in a cell within the selected home range. In this study, the model values were the joint occurrence of waste area contamination and habitat use. A circular sampling unit (hypothetical home range ellipse) was used to deal with the problem of potential directional bias of simulated home ranges in selecting overlapped core areas to be used in calculating exposure (Marinussen and van der Zee, 1996). Since the spatial distribution of habitat use was known (i.e., the probability resource selection model), a uniform PDF (rather than a non-uniform) PDF could be used. The simulation is expressed in the following steps (Fig. 4a):

1. The desired waste site(s) or sources of contamination to be modelled were identified. Because of the nature of contamination, and the spatial relationship between the home range of the species and the waste site(s), buffering of the waste sites was necessary to extend the risk of exposure by an a priori thresh-

old of distance. This supplies a dynamic area–home range ratio (Eq. (1)).

2. Based on the home range information derived from the telemetry data, a circular home range was used. The waste site was buffered using a radius of 90% of the home range. This parameter can be modified based on user input/a priori knowledge about the species.

3. A Monte Carlo simulation was performed to simulate the risk of exposure of the population to the contamination in an iterative fashion. For each iteration, a circular home range was randomly created across the space with the constraint that its centroid was inside the buffered waste site. The home range was then used to spatially query the probability values of all core areas that were located within. An area-weighted average probability (P) was computed for all selected core areas. By using the intersection rule of topological operation, the area of (buffered) waste site(s) that lies within the home range (HR) could be calculated. With known information about the total number of ingested media (m), the ingestion rate (IR_i) and the concentration of contaminant j in medium i (C_{ij}), and the body weight of the endpoint species (BW) from the field data or previous literature, the total exposure (E_j) was computed (Eq. (1); Gaines et al., 2004; Gaines et al., 2005). This procedure was performed 30,000 times for both the Tims Branch and the Steeds Pond sites. The procedure provides an estimate of the underlying distribution of a raccoon's exposure at the two sites. The histogram of the 30,000 simulated exposures provides a visual approximation to the distribution. The quantiles of the ranked exposures are unbiased estimates of the true population quantiles.

Often investigators are interested in making inferences about the mean exposure at a waste site, but we can almost never assume that the distribution of the mean is the same as that of the population. Hence, we need to perform a similar procedure to estimate the distribution of mean exposure. Earlier studies showed that a population of approximately 30 raccoons occupies the Tims Branch site and approximately 10 at the Steeds Pond site (Boring, 2001; Gaines, 2003). Hence, we randomly sample 30 home ranges for Tims Branch and 10 home ranges for Steeds Pond, estimate the 30 (or 10) exposures and take the average. This procedure
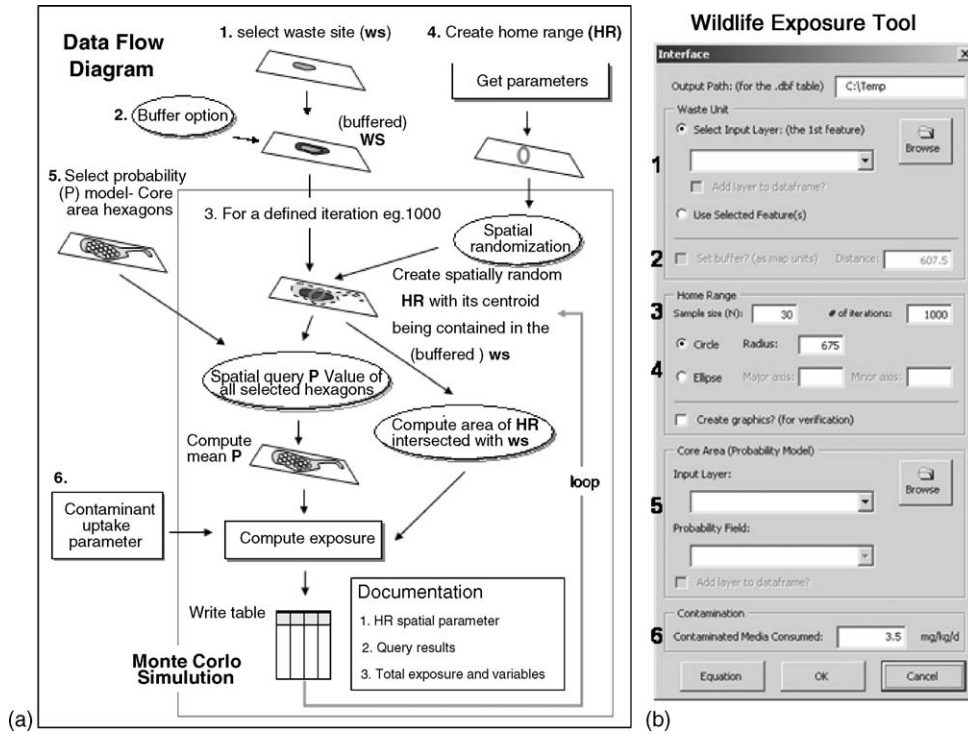
Fig. 4. (a) A data processing flow diagram of the Monte Carlo simulation for exposure estimation. (b) The graphic user interface of the proposed wildlife exposure tool.

is repeated 1000 times for each site. This produces a Monte Carlo random sample of average exposures. As above, the resulting 1000 means provide an estimate of the distribution of mean exposure using histograms and quantiles. The 2.5th and 97.5th elements in the ranked data vector of means are the estimated lower and upper bounds, respectively, of the 95% confidence interval. The mean exposures and their corresponding 95% confidence intervals provide the information necessary to conduct hypothesis testing about the mean exposure at the waste units. In practice, a researcher could test the hypothesis that the mean exposure was zero, or below (above) a given regulatory limit by using the appropriate confidence bound (upper or lower).

3.4. Graphical user interface

For practical purposes, the model was implemented as a dynamic linked library (DLL) in Environmental Systems Research Institute (ESRI$^{©}$) ArcMap (the GIS used by the DOE) using Visual Basic. The graphi-

cal user interface (GUI) tool utilizes forms and the associate objects (e.g., combo boxes) to allow user interactions (Fig. 4b). The user is allowed to select input GIS data layers directly from the current data frames or browse from existing datasets. Specific instructions and the data processing flow diagram are also provided in the tool for intuitive learning.

Users have the flexibility in defining single or multiple waste sites as sources of contamination. As noted in the previous section, the optional buffering feature takes local population risk from contaminants into consideration by simulating many hypothetical home ranges near the waste site instead of merely focusing on a central location of one animal's possible home range, hence leading to a more realistic estimation of total exposure. The buffering option also allows the centroids of the species' home range to be positioned beyond the boundary of the waste site(s). This extends the model's capability by allowing the species' home range to overlap a small portion with the waste site(s) thus providing

an entire distribution that estimates exposure (Fig. 5). It was assumed that the users have a priori information about the contaminant of concern in deciding a distance threshold in buffering the waste site(s). This is the norm for DOE-based risk assessments. The user is required to input the dimensions (e.g., radius) of the circular home range in the textboxes available. Similar to selecting a waste site(s), the users can either select or browse for an existing probability data layer that represents the likelihood of the species in the defined core areas (Gaines et al., 2005; Gaines, 2003). Contamination information for all media of a species (e.g., number of ingested media, ingestion rate, concentration level, body weight) must be preprocessed and input as a lumped value. This information is available for DOE risk assessors and was computed from

empirical data for this demonstration (Gaines, 2003). The modelling tool was designed to ultimately allow direct linkages to a list of media in an existing table or spreadsheet.

The model output was created in a dBase table (dbf). The output consists of a table of estimated exposure (E_j) from the Monte Carlo simulation and a summary table that stores the mean exposure of every 1000-iterations. By using built-in functions available in ArcMap, the set of estimated exposure values can be summarized to create a histogram, which aids interpretation and further analysis of the PDF of the modelled total exposure. For verification purposes, the spatial parameters used for each randomly generated home range, query results, and all variables used in Eq. (1) are also stored in the output.
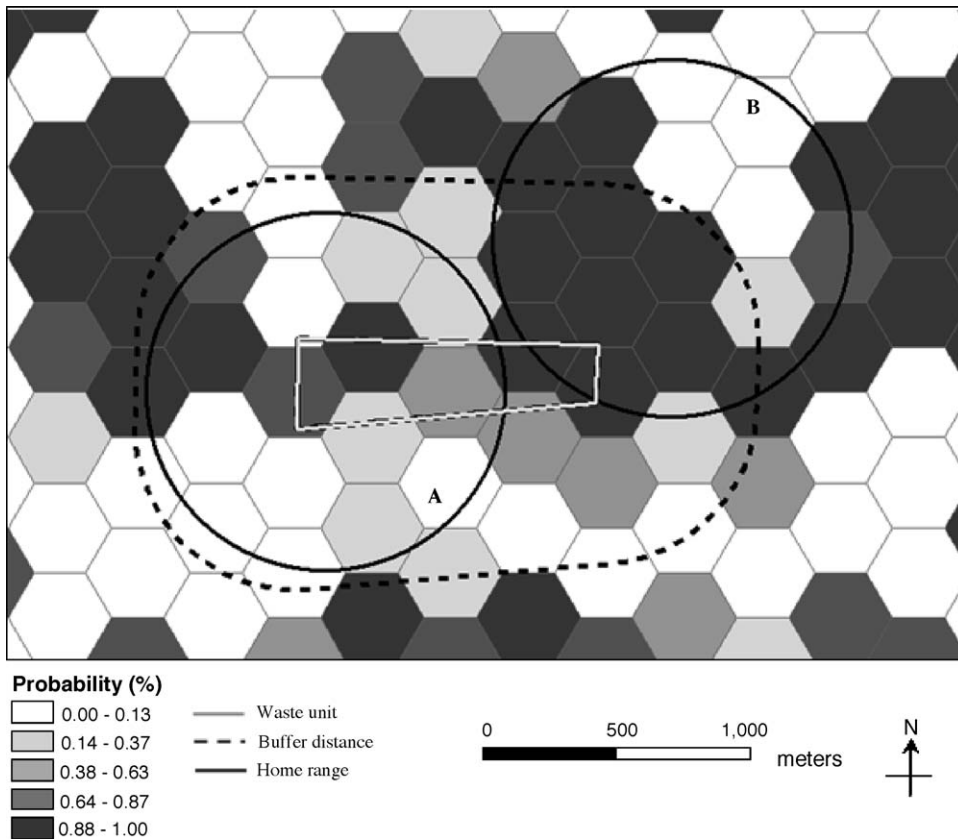

Fig. 5. Two random home ranges created to model the uranium exposure to raccoons from the waste unit. Home range A was created with its centroid within the boundary of the waste unit while home range B was created with its centroid outside the waste unit boundary but inside the buffered waste site (buffer distance of 90% of home range).

4. Results

The best logistic regression model was selected for minimizing error in predicting locations that were known to be used by raccoons based on observational data (Table 1). As populations are generally sampled rather than completely observed, it is difficult to ascertain that individuals have never/will never use a specific location. However, observing an individual using a location is thus, more certain (assuming the observational method is reliable) (Hodgson et al., 1988). When creating a model for predicting use/non-use of a spatial location the model can always be parameterized to minimize omission errors at the expense of incurring more commission errors. One-hundred percent omission accuracies can result from a very conservative parameterization (although typically very high commission errors will occur). The model parameterization approach is a careful balance of the known reliability of the observations. Thus, our regression model was somewhat biased toward the reliability of our data and was expected to be a better predictor of habitats used. However, the home range study coupled with the hexagonal mesh approach gave the best assessment of quantifying habitats that were not used by raccoons. A leave-one-out cross-validation approach was used to determine the overall accuracy of the habitat model for predicting the use and non-use of locations by raccoons. This approach iteratively drops one observation at a time, and predicts the missing observation using the fitted model. This is repeated for each observation in the data set. The validation results were 62 and 100% accurate for predicting non-used and used locations, respectively. Not surprisingly, the best predictive variables with positive associations with raccoon use were floodplain oak forests and evergreen hardwoods (i.e., cypress) (Table 1). The best negatively associated variables were upland oak hardwoods, upland scrub forests, dense-canopy pines, and water/marsh.

The general framework and specific procedures described above were applied to the Steeds Pond and Tims Branch depositional waste sites. The results presented in this paper document the expected exposure of raccoons to U contamination from this site. The raccoon population modelled in this simulation includes only those that would visit the site.

Based on home range calculations for raccoon populations on the SRS (Boring, 2001), the model used a

Table 2
Monte Carlo exposure estimates for the populations at Tims Branch and Steeds Pond

Variable	Monte Carlo estimate
Tims Branch	
Population mean	0.3779
Population standard deviation	0.3192
0.025 and 0.975 quantiles of distribution	(0.0159, 1.3910)
Steeds Pond	
Population mean	0.0686
Population standard deviation	0.0362
0.025 and 0.975 quantiles of distribution	(0.0052, 0.1200)

circular home range with a radius of 675 m. A buffer distance of 90% of the original home range radius (i.e., 607.5 m) was used to include randomly located home ranges surrounding the waste site. This allowed the simulation to include animals within a population whose home range partially overlaps with the waste site. For illustration purposes, Fig. 5 presents the map of home ranges created in two iterations. A lumped value of the contaminated media consumed was assumed to be 3.5 mg/kg/day for potential U uptake of the species. This amount was based on raccoon food items collected at each waste site (see Sample and Suter, 1994 for specific allometric equations; see Gaines, 2003 for applications using a resource selection model). Since Steeds Pond is within the Tims Branch depositional system, a single value could be used.

In Tims Branch, the total exposure frequency distribution was positively skewed (Fig. 6a). Exposure amounts ranged up to 1.41 mg/kg/day. The mean probability of the species inhabiting the area surrounding Tims Branch remains relatively low, particularly to the west of Tims Branch (Fig. 3). Thus, a positively skewed distribution is not surprising for an isolated waste site.

Unlike Tims Branch, the total exposure frequency distribution was more uniform in Steed's Pond (Fig. 6b). Exposure amounts ranged up to 0.13 mg/kg/day. Predicated raccoon use around Steed's Pond was more uniform than around Tims Branch (Fig. 3). Population mean, standard deviation and 95% confidence bounds for both sites are shown in Table 2. However, the numeric values of the frequency distribution of Steed's Pond were much lower than Tims Branch. This is because the home range size is much
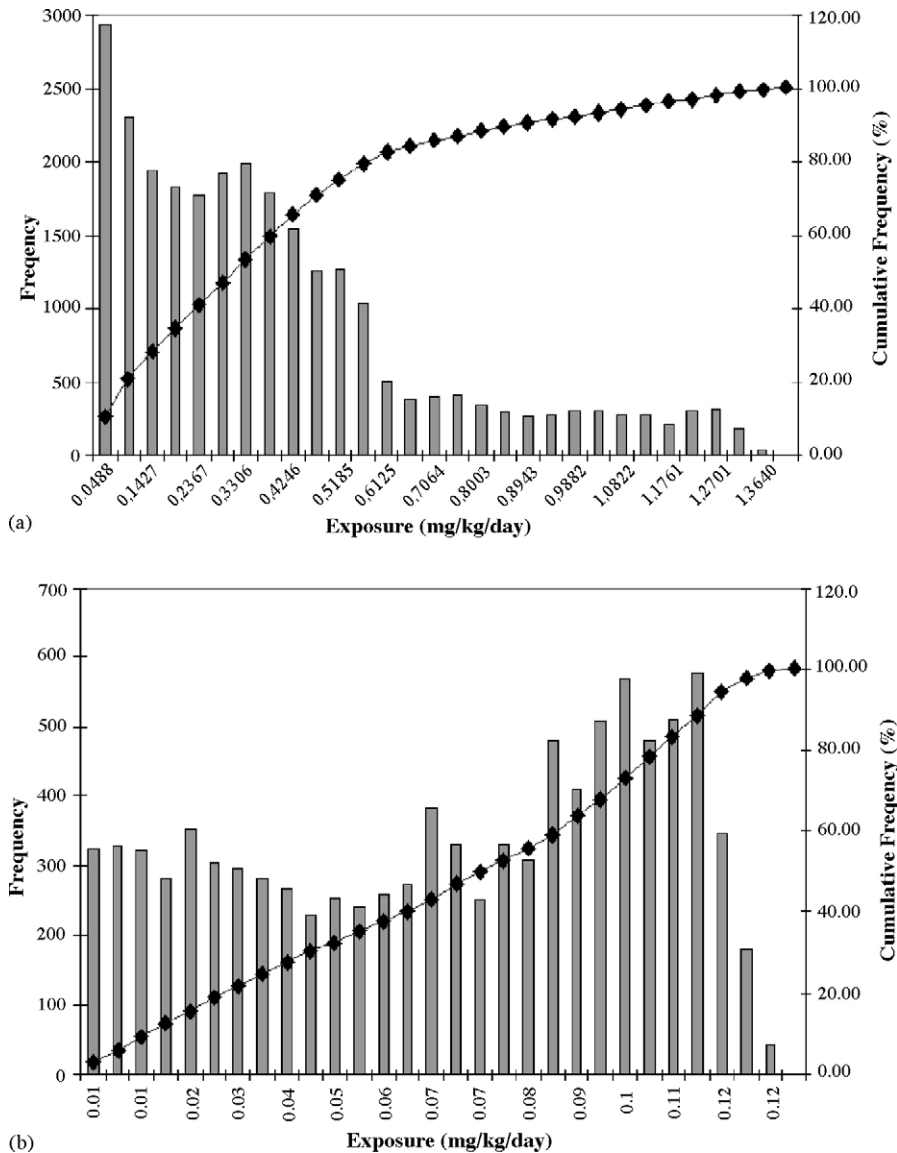
Fig. 6. Histogram of the frequency distribution of uranium exposure and its cumulative frequency percentage at (a) Tims Branch, (b) Steed's Pond.

larger than the area of Steed's Pond, which lowers the ratio of waste site area within the home range and home range area in the exposure estimation.

For both sites, the Monte Carlo results for mean exposure are shown in Table 3. Mean exposure estimates for Steeds Pond and Tims Branch are 0.3752 and 0.0686 mg/kg/day, respectively. Histograms of the Monte Carlo means are shown in Fig. 7a and b. As a

Table 3
Monte Carlo exposure estimates for the mean exposure

Site	Mean exposure	95% confidence interval
Tims ranch	0.3752	(0.2602, 0.5023)
Steed's pond	0.0686	(0.0463, 0.0905)

result of the uniform PDF of random ellipse centroids, the histogram of the simulated mean exposures appears to be much closer to the normal distribution than the underlying population. Also as expected, the 2.5th and 97.5th percentiles for the mean (shown as 95% confidence bounds) are much tighter than for the highly variable underlying population.

5. Discussion

The developed exposure model is a complex spatially explicit model that is composed of resource selection functions, contaminant exposure modelling and simulation modelling. Like all models, the framework is an attempt to simulate reality with certain simplifications and underlying assumptions. It is, thus, useful to discuss the limitations of implementing such a spatially explicit ecological model.

Many studies have described spatial characteristics, such as edge effects, patch size and shape and overall landscape heterogeneity as important factors in controlling ecological processes within a fragmented landscape (Haefner et al., 1991; Laurance and Yensen, 1991; Zheng and Chen, 2000). This study used a hexagonal mesh rather than the traditional square tessellation as the hexagon has an intrinsic advantage that all neighboring cells are equidistant from the centroid of the center cell. Moreover, a hexagonal tesselation contributes to a lower edge effect (e.g., edge/area ratio) that closely approximates a circle and can still represent a matrix without any edge mismatch. However, the exposure estimation will still suffer from an edge effect if the waste site is located "too close" to the boundary of the habitat use probability model (i.e., hexagonal mesh) relative to its home range size. For efficiency purposes, the strategy adopted in this study for this edge problem was to use mean area-weighted probability among the selected core areas within the hypothetical home range polygons. The Monte Carlo simulation also helps to minimize the bias by ensuring enough spatial samples from all directions. Other alternatives may include spatial extrapolation, quantification of edge effects and delineation area of edge influence (Zheng and Chen, 2000).

The effect of spatial aggregation has long been known as an important issue in any kind of ecological analysis and assessment (Clark and Avery, 1976;

Marinussen and van der Zee, 1996). In this research, the scale of a raccoon's home range and core area (i.e., size of a hexagon) had been defined under careful consideration and testing. Home range was determined based on the procedures described in the previous section. Core areas of 3.24, 10 and 15 ha, had also been tested in developing the probability resources selection model. As noted, 3.24 ha is the maximum triangulation error for the telemetry data (Boring, 2001), while 10 and 15 ha are the average size of the 30 and 50% core areas found within the raccoon's home range, respectively. Previous analysis showed that 10 ha model was most appropriate among the three scales (Gaines, 2003). Inappropriate scale in representing the probability resources selection model would lower the overall accuracy in predicting the likelihood of raccoon's presence across space. This may further lead to unreliable results in modelling exposure and hence poor decision made based on the information. Therefore, similar attempts in using home range/core area of another species for ERA must carefully choose the appropriate scale for that particular ecosystem.

Precision is yet another spatial issue to consider. In this research, each 10 ha core area is represented by a single value in a hexagon to indicate the likelihood of raccoons occupying that particular habitat. However, the accuracy of the final exposure estimation might be sensitive to rapid spatial changes in habitat use. Different habitat use estimations may result from different origins for the tessellation. This origin problem is not inherent in the exposure estimation using a Monte Carlo simulation. However, this origin effect will be true for either grid or hexagonal tessellations.

This research used a circular home range to avoid directional bias in the process of spatial sampling. However, other shapes of home range might be desired in some cases. For example, a raccoon is known for favoring prey along wooded areas with streams, rivers and lakes. An elliptical home range oriented parallel to the water body might better represent the likelihood of raccoons in using that kind of habitat. This would affect the spatial sampling and hence the final exposure estimation to the contaminants. Future versions of this model will employ such home range geometries. A major consideration of the ecological validity of this modelling effort is the choice of the receptor species to be modelled and using the proper hypothetical home range size. For example, although raccoons
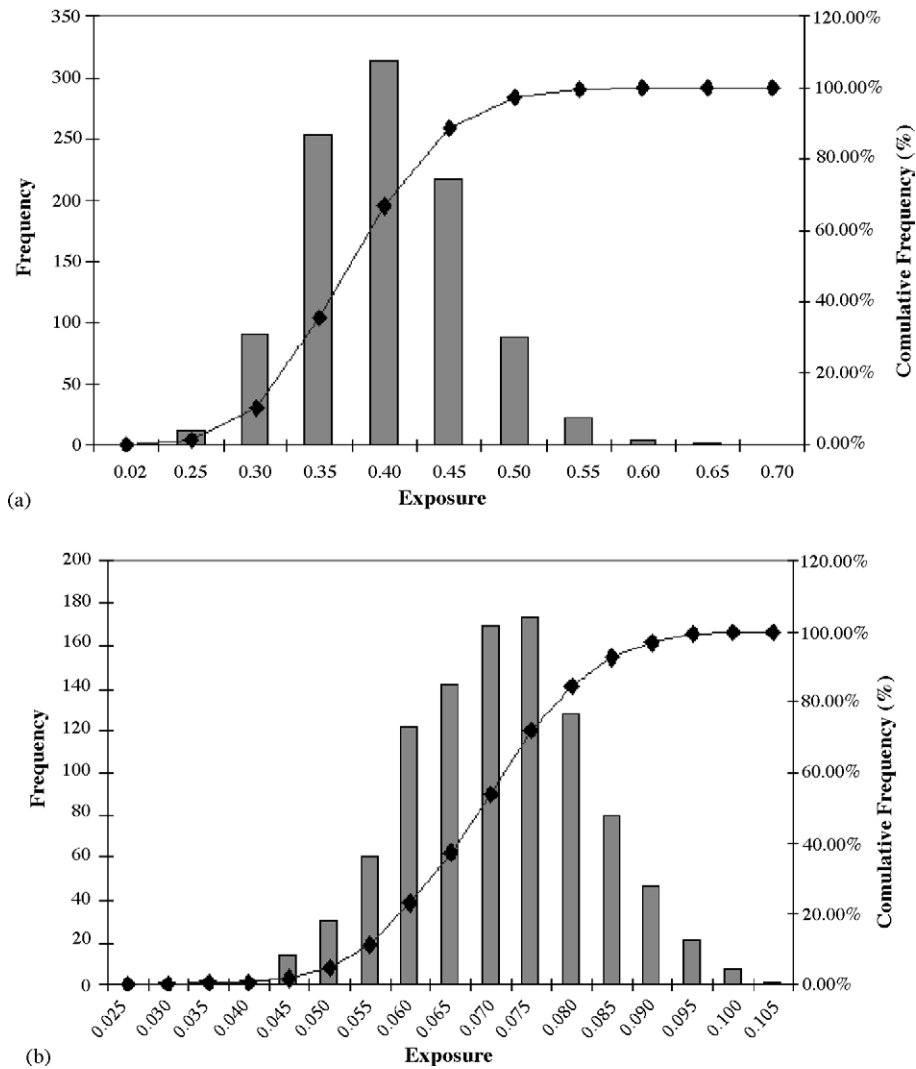
Fig. 7. Histogram of bootstrapped mean exposure of (a) 30 simulated raccoons at Tims Branch, and (b) 10 simulated raccoons at Steed's Pond.

are generally found throughout the SRS, there are inherently areas that they will avoid such as large upland pine habitats. Therefore merely querying the GIS data layer of the raccoon habitat predictor portion of the exposure model would identify those areas before a full randomization would be employed. Following this logic, an individual's home range size may vary based on available resources (e.g., larger home ranges in areas with fewer resources). These parameters must be considered prior to the implementation of the simulation modelling, and can be easily done by querying the

hexagonal units near the focal waste sites. However, using habitat generalists such as the raccoon as focal receptor species can minimize these potential errors.

The goal of this article was to provide a general framework for GIS-based exposure modelling for ERA. Any ecological assessment that implements GIS must consider the issues above and take into consideration the model assumptions and solutions to those issues. The elements of concern for Tims Branch are U and Ni, as well as other heavy metals (Punshon et al., 2003a,b). Both U and Ni have been shown to be

bioavailable to small mammals in this system (Punshon et al., 2003b). Murray (2003) has shown that availability of metals in Tims Branch may also have been influenced by the relative trophic position of primary and secondary consumers. However, the dynamics of the Tims Branch food web have still not been entirely defined. Undoubtedly, raccoons are an integral part of the community structure of Tims branch and the population has a very high risk of exposure and subsequent uptake based on their feeding habits. Further, Murray (2003) also showed that the presence of U in muscle tissue in water snakes (*Nerodia* spp.) correlated to DNA double-strand breakage, re-emphasizing that although U and other potentially toxic metals may not biomagnify or even bioaccumulate in high levels, they must be monitored from a hierchical ecosystem approach rather than at the compartment level. Using an exposure assessment helps identify these potential risks.

Based on the EPA's Integrated Risk Information System (IRIS), neither a reference dose (RfD) nor a reference concentration (RfC) has been derived for U (IRIS, 1997). However, the US Department of Health and Human Services, through the Agency for Toxic Substances and Disease Registry (ATSDR) has published a toxicological profile for U (ATSDR, 1999) and a minimal risk level (MRL) of 2.0×10^{-3} mg/kg/day has been derived for intermediate-duration oral exposure (protective for chronic-duration oral exposure) to soluble compounds of U based on a LOAEL of 0.05 mg U/kg/day d for renal effects in rabbits (Gilman et al., 1998). If the U is in an insoluble form, the risk would be lower (ATSDR, 1999). This MRL is a protective level for humans and not raccoons; however the predicted exposure risk to raccoons exceeds this limit as well as the LOAEL for rabbits. Bertsch et al. (1994) showed that the U in soil in Tims Branch was in a soluble form. However, current studies (Savannah River Ecology Laboratory, unpublished data) have shown that solubility may change through the trophic media. Specifically, insoluble U may be somewhat soluble when ingested, depending on the solubility characteristics of the U salt. That is, the solubility and thus the toxicity of U lies in predicting what fraction of U might be soluble in the gut which would entail using "simulated" gastric solutions to assess solubility from various matrices upon ingestion. Future research must focus on understanding how U move through these environmental matrices in relation to trophic compartmental exposure.

6. Conclusion

The habitat and exposure model developed in this study can be used as a template for ERA and environmental management. The model incorporated GIS, resource selection functions and simulation to analyze a population distribution, identify areas of concern, and quantify the risk of exposure of an indicator species to particular waste site(s). With careful consideration of the spatial issues discussed above, this model can be extended to other receptor species for a variety of waste sites. Future research can be directed towards extending the model to address assumptions adopted in this research. It will also be useful to validate the exposure estimates based on long-term data of the body burden of raccoons for known contaminants.

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