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Spatial Variability and Uncertainty in Ecological Risk Assessment: A Case Study on the Potential Risk of Cadmium for the Little Owl in a Dutch River Flood Plain

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This paper outlines a procedure that quantifies the impact of different sources of spatial variability and uncertainty on ecological risk estimates. The procedure is illustrated in a case study that estimates the risks of cadmium for a little owl (*Athene noctua vidalli*) living in a Dutch river flood plain along the river Rhine. A geographical information system (GIS) was used to quantify spatial variability in contaminant concentrations and habitats. It was combined with an exposure and effect model that uses Monte Carlo simulation to quantify parameter uncertainty. Spatial model uncertainty was assessed by the application of two different spatial interpolation methods (classification and kriging) and foraging ranges. The results of the case study show that parameter uncertainty is the main type of uncertainty influencing the risk estimate, and to a lesser extent spatial variability, while spatial model uncertainty was of minor importance. Compared to the deterministically calculated hazard index for the little owl (0.9), inclusion of spatial variability resulted in a median hazard index that can vary between 0.8 and 1.4. It is concluded that a single estimator for a whole flood plain may over- or underestimate risks for specific parts within the flood plain. Further research that expands the procedure presented in this paper is necessary to improve the incorporation of spatial factors in ecological risk assessment.

Introduction

Over the past decades, the river Rhine has been heavily polluted with toxic substances (e.g., heavy metals and polyaromatic hydrocarbons) from industrial and municipal discharges and agricultural activities. The impact of this pollution on riverine ecosystems in the Dutch delta is widely recognized (*1*). The diffuse contamination of the Rhine flood plains is characterized by high spatial and temporal variability, which is related to both natural processes (sedimentation, erosion, resuspension) and human influences (extraction of gravel, sand, and clay, construction of embankments and weirs). To deal with the future effects of climate change and increasing urbanization, a new form of adaptive river management is adopted in The Netherlands. For example, more space is created for water storage and nature reserves, while the current agricultural function of the flood plains is greatly reduced (*2*). However, development of new nature areas can only be successful if the risks posed by the contaminants to wildlife and their prey items are within acceptable limits. Proper methods for ecological risk assessment are necessary to evaluate these risks.

Several studies (*3*−*6*) have indicated that the relative spatial positions of receptors and contaminated media can strongly influence estimates of exposure and hence of risk. Inclusion of the spatial relationship of receptors, their habitats, and contaminants can result in more representative, and possibly more ecologically relevant, risk assessments (*7*−*9*). In addition, location-specific risk estimates can assist in identifying locations where remedial efforts should be focused and evaluate *ex ante* alternative remedial strategies (*4*, *5*). Geographical information systems (GIS) can be a helpful tool to include spatial components in ecological risk assessment (*3*, *5*, *10*, *11*).

In a previous paper, Kooistra et al. (*12*) proposed a procedure to include spatial components in an ecological risk assessment of river flood plains. By linking a GIS with an exposure model, spatial aspects such as variability of contamination concentration and foraging range were taken into account. The procedure was applied to quantify the impact of spatial variation on the exposure of the little owl (*Athene noctua vidalli*), common shrew (*Sorex araneus*), and field vole (*Microtus agrestis*) to cadmium (Cd), copper (Cu), and zinc (Zn) in a river flood plain along the river Rhine in The Netherlands. Site-specific risk maps showed that Cd may cause high potential risks for these species for several areas within the flood plain. However, this study did not investigate the relative importance of including spatial variability in the risk assessment compared to other sources of variability and uncertainty.

It is important to distinguish the influence of variability and uncertainty on model outcomes (*13*). While spatial variability is irreducible and also scale dependent, uncertainty can be reduced, for instance, by better measurement techniques or by including more aspects of the real world in the model (*14*). This implies that the variance in model outcomes due to spatial variability may have different implications for decision making compared to the variance caused by uncertainty. Here, we specify uncertainty as parameter uncertainty, reflecting incomplete knowledge of input data, and model uncertainty, introduced by disregarding potentially relevant aspects of the real world (*15*).

The present paper outlines a procedure that quantifies and compares the impact of different sources of spatial variability and uncertainty on ecological risk estimates. The procedure is illustrated in a case study that estimates the risks of cadmium in a heterogeneously contaminated river flood plain along the river Rhine in The Netherlands to a terrestrial food web with the little owl as a top predator. The aim of the case study is to determine the relative importance

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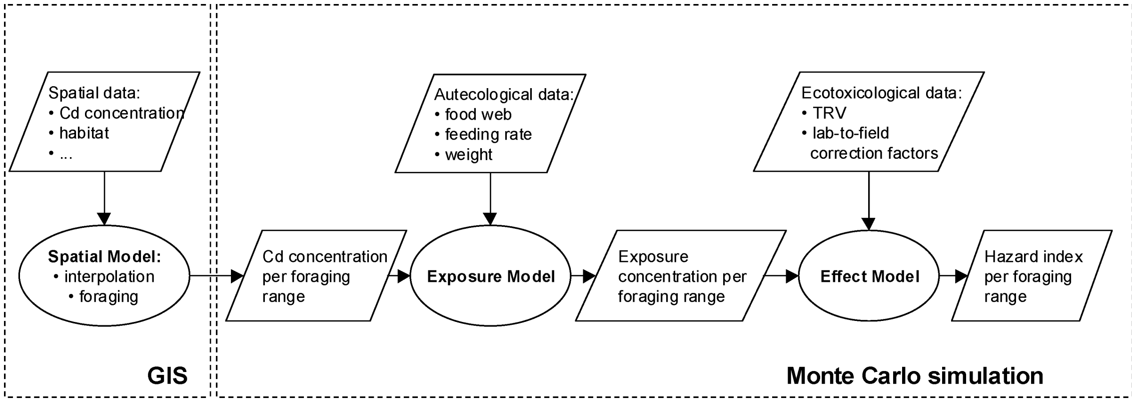

FIGURE 1. Schematic overview of the conceptual model for the incorporation of spatial components in the ecological risk assessment of river flood plains.

of spatial variability in the ecological risk estimates compared to other sources of variability and uncertainty. A distinction is made between (a) spatial variability in contaminant and habitat distribution, (b) model uncertainty related to the choice of a spatial interpolation method and the extent of the foraging range for the focal species, and (c) parameter uncertainty in soil concentrations, food web relationships, and lab-to-field extrapolation of toxicity tests. The possibilities for general application of the presented methodology and the implications of the case study results for flood plain management are discussed.

Materials and Methods

Outline of Procedure. The approach used for spatially explicit modelling of ecological risks is based on a procedure developed by Kooistra et al. (*12*). The procedure links the spatial analysis capabilities of GIS with mathematical models that estimate exposure and effect for a terrestrial food web (Figure 1). In addition to the spatial variability of the contaminant concentration that was included in the original procedure, the present study also includes the spatial variability of habitat suitability for prey items. Within the GIS, contamination maps are produced using interpolation methods and combined with a spatially explicit foraging model. This results in a probability distribution of the soil Cd concentration for each foraging area of the little owl.

The procedure then applies an exposure model that models bioaccumulation of Cd from the soil through a terrestrial food web with the little owl as top predator. For this purpose, the original exposure model (*12*) was updated with recent food web relations. In addition, an effect model was used that extrapolates laboratory toxicity data to field conditions, accounting for several factors that may affect exposure and sensitivity (e.g., caloric content of food and food assimilation efficiency) (*16*). The exposure and effect model can be run in a deterministic mode, resulting in point estimates, as well as in a probabilistic mode, incorporating distributions for input parameters and resulting in an output distribution for potential Cd risks. Within the probabilistic mode, Monte Carlo simulation is used to evaluate the contribution of spatial variability and parameter uncertainty on the ecological risk estimates.

The area selected for the case study is the Afferdensche and Deestsche Waarden flood plain. This flood plain with an area of 250 ha is located along the river Waal, the main branch of the river Rhine in The Netherlands (Figure 2). Deposition of contaminated sediment has resulted in elevated concentrations of heavy metals in the soil. The case study concentrates on Cd because it has a relatively high accumulation potential and may pose high risk to wildlife. The little owl was selected as end-point species for the assessment because (a) it is a characteristic and endangered breeding bird in flood plains, (b) it is present in the territory the entire year, resulting in chronic exposure, and (c) it is a predatory bird foraging on species (e.g., earthworms, common shrew) with a relatively high accumulation potential for Cd (*17*). Potential risks of Cd contamination for the little owl are evaluated under the assumption of no flooding (e.g., in the summer season).

Soil Concentrations. A key input parameter for the ecological risk assessment is the total Cd concentration in milligrams per kilogram dry weight of soil. From three previous studies (*12*, *18*, *19*), a GIS database was available describing 102 soil sampling locations for which Cd concentrations were determined (Figure 2). For all locations the top soil (0−10 cm) was sampled. Measured values for the total Cd concentration show a skewed distribution with a range between 0.1 and 11.1 mg/kg of dry weight and a mean value of 3.7 mg/kg of dry weight.

The measured Cd concentration in the 102 sampling locations were converted into continuous Cd concentration maps using two different interpolation techniques (*20*). The performance of a geostatistical method (kriging) was compared with a global interpolation method (classification in homogeneous units). This is explained in more detail in the section on spatial model uncertainty.

Foraging Behavior. A step often disregarded in ecological risk assessment is the spatial dimension of foraging behaviour (*21*). During their search for food, organisms integrate exposure to different contaminant concentrations over space and time. The little owl is a receptor that is able to transit local nonforaging areas to reach suitable areas (*7*). Small mammals (e.g., field vole, common shrew) that have their main habitat in grassland areas are the main food source for the little owl (*22*). Potential foraging areas for the little owl were derived from a map presenting the main river ecotopes within the Afferdensche and Deestsche Waarden flood plain. In the Dutch river ecotope classification system, an ecotope is defined as a spatial unit which is homogeneous as to vegetation structure, succession stage, and main abiotic factors (*23*). Ecotopes that consist of natural or agricultural grassland were chosen as foraging area (Figure 2). It was assumed that the little owl only forages up to a certain distance from its nest. The range for its foraging circle will depend on the prey density and is treated as a source of spatial model uncertainty.

To estimate site-specific risks, GIS (Arcview version 3.1 [*24*]) was used to overlay a grid of regularly spaced points on the soil contamination maps. Each point was considered to represent the center (e.g., nest) of a potential foraging area for the little owl. The procedure resulted in 107 potential foraging areas for the little owl within the flood plain. For each foraging area, the Cd exposure concentration was determined by calculating the area-weighted average soil

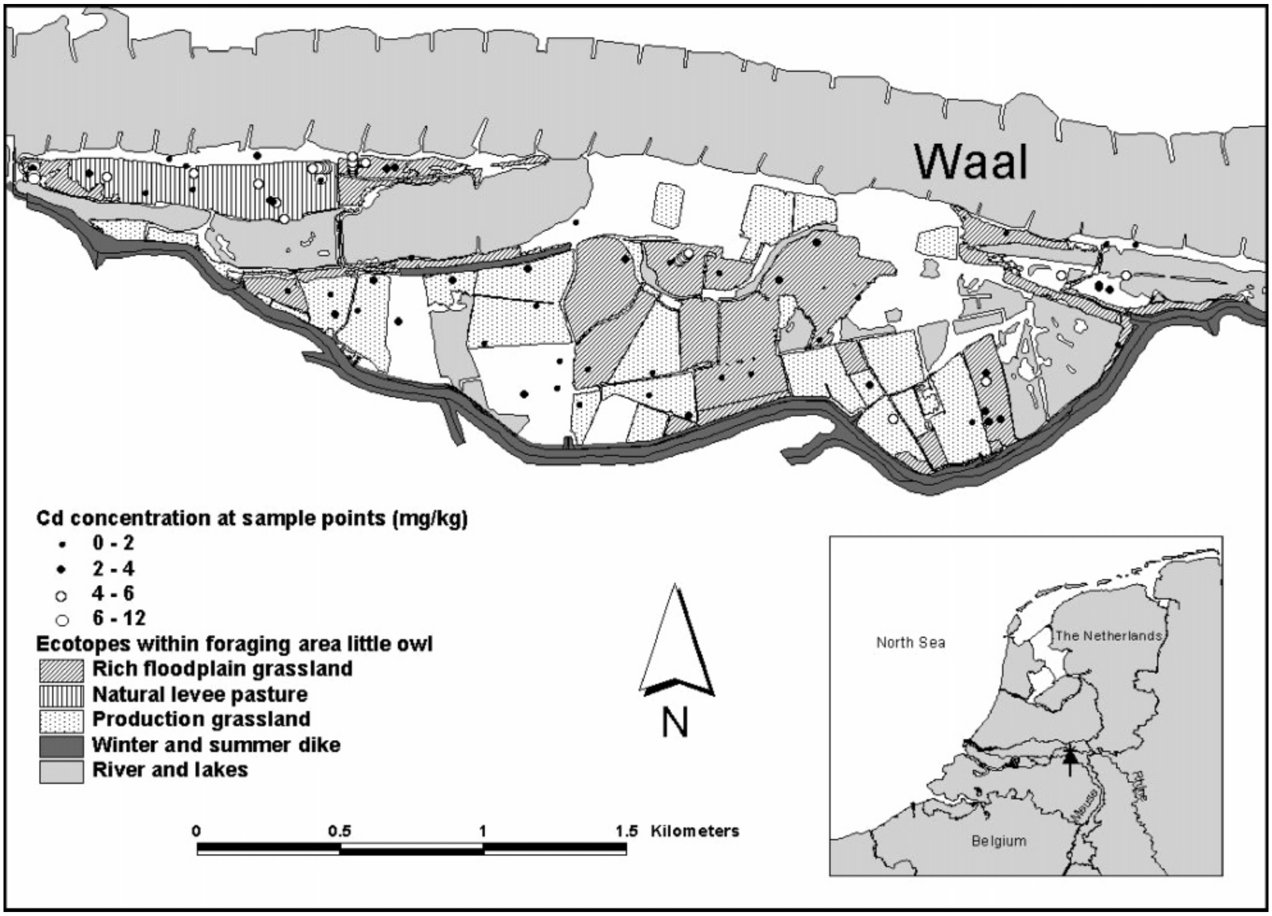

FIGURE 2. Overview of the location of available point contamination samples and the distribution of suitable habitat for the little owl within the Afferdensche and Deestsche Waarden flood plain (situation 1998). The inset shows the position of the flood plain along the river Waal in The Netherlands.

Cd concentration (Cs_w in mg/kg of dry weight) in suitable ecotopes:

$$Cs_w = \frac{1}{\sum_i A_i} \cdot \sum_{i=1}^{n} A_i \cdot Cs_i \qquad (1)$$

where Cs_i is the contaminant concentration in soil contamination unit i (mg/kg of dry weight), A_i is the area of soil contamination unit i within the foraging area, and n is the number of soil contamination units within the foraging area in suitable ecotopes. Cs_w was used as input for the exposure model.

Exposure Model. A food web-based model was used to estimate Cd exposure of the little owl. Two exposure routes were considered: (1) ingestion of contaminated soil and (2) ingestion of contaminated food (prey) or forage (via plant uptake of contaminants). The little owl and six other species were incorporated into a flood plain-specific terrestrial food web (*17*). The field vole (*Microtus agrestis*) is an herbivorous ground-dwelling mammal in intimate contact with contaminated soils and a potentially significant fraction of the little owl diet. The common shrew (*Sorex araneus*) is a carnivorous small mammal and consumer of invertebrates such as spiders, beetles, and earthworms. Beetles and earthworms are also directly part of the little owl's diet. The input data for the exposure model are given in Table 1. Fixed subscript numbers are used throughout this paper to refer to the individual components of the food web (see legend of Table 1). Parameters specific for riverine ecosystems were applied as much as possible, except for some generic parameters, such as water proportions in biota, where general literature values were used.

Values for plant-soil bioconcentration of Cd in above-ground plants parts for several plant species in flood plains along the river Meuse in The Netherlands were taken from Verkleij et al. (*25*). The resulting bioconcentration factors were used to calculate the Cd concentration in above-ground plant tissue (Ct_2 in mg/kg of dry weight plant):

$$Ct_2 = Cs_w \times BCF_2 \qquad (2)$$

where BCF_2 is the bioconcentration factor of Cd for vegetation (kg of dry weight soil/kg of dry weight plant).

Cd body concentrations in invertebrate species (Ct_i in mg/kg of dry weight tissue) were calculated, using a regression method described by Heikens et al. (*32*):

$$\log(Ct_i) = \log a + b \times \log(Cs) \qquad (3)$$

where a and b are the regression coefficients. Regression data for beetle and spider were taken from Heikens et al. (*32*). For earthworm, a flood plain specific regression equation was taken from Ma et al. (*33*). The regression coefficients used are presented in Table 2.

For bioaccumulation of Cd in field vole and common shrew, regression equations between estimated daily intake and measured Cd concentrations in liver and kidney were used (*34*). On the basis of the Cd concentration in food, thedaily estimated intake (D_i in mg/kg body dry weight/day)

TABLE 1. Input Parameters Used for the Exposure and Effect Model Calculations

description of variable	symbol[a]	units	point estimate	distribution parameters[b]	source
proportion of water in soil	P_1	unitless	0.29	normal (0.29, 0.09)	18, 19
bioconcentration factor plant parts	BCF_2	kg soil/kg plant	0.37	log-normal (0.37, 0.57)	25
proportion of water in plant tissue	P_2	unitless	0.915	normal (0.92, 0.02)	26
proportion of water in earthworm tissue	P_3	unitless	0.82	normal (0.82, 0.018)	26
proportion of water in beetle tissue	P_4	unitless	0.711	normal (0.71, 0.089)	26
proportion of water in spider tissue	P_5	unitless	0.697	normal (0.70, 0.070)	26
proportion of liver in total vole body weight	$Fe_{6,I}$	unitless	0.054	normal (0.054, 0.0034)	*c*
proportion of kidney in total vole body weight	$Fe_{6,II}$	unitless	0.013	normal (0.013, 0.0037)	*c*
proportion of total Cd body burden in liver and kidney	Fb_6	unitless	0.8	beta (6.7, 2.2, 1)	26, 27
fraction of soil in vole diet	$Fr_{1,6}$	unitless	0.02	beta (1.5, 5.3, 0.1)	28
fraction of plant tissue in vole diet	$Fr_{2,6}$	unitless	0.98	beta (1.5, 0,25, 1)	29
feeding rate of vole	IR_6	g/day	12.0	log-normal (12, 1.2)	30
body weight of vole	W_6	g	20.87	log-normal (20.9, 1.33)	29
proportion of water in vole tissue	P_6	unitless	0.73	normal (0.73, 0.076)	26
proportion of liver in total shrew body weight	$Fe_{7,I}$	unitless	0.07	normal (0.070, 0.0048)	*c*
proportion of kidney in total shrew body weight	$Fe_{7,II}$	unitless	0.019	normal (0.019, 0.0033)	*c*
proportion of total Cd body burden in liver and kidney	Fb_7	unitless	0.8	beta (6.7, 2.2, 1)	26, 27
fraction soil in shrew diet	$Fr_{1,7}$	unitless	0.02	beta (1.5, 5.3, 0.1)	28
fraction of earthworm tissue in shrew diet	$Fr_{3,7}$	unitless	0.51	beta (1.5, 1.47, 1)	29
fraction of beetle tissue in shrew diet	$Fr_{4,7}$	unitless	0.29	beta (1.5, 3.6, 1)	29
fraction of spider tissue in shrew diet	$Fr_{5,7}$	unitless	0.18	beta (1.5, 6.8, 1)	29
feeding rate of shrew	IR_7	g/day	2.8	log-normal (2.8, 0.3)	30
body weight of shrew	W_7	g	7.15	log-normal (7.2, 0.27)	29
proportion of water in shrew tissue	P_7	unitless	0.73	normal (0.73, 0.076)	26
fraction soil in little owl diet	$Fr_{1,8}$	unitless	0.02	beta (1.5, 5.3, 0.1)	28
fraction of earthworm tissue in little owl diet	$Fr_{3,8}$	unitless	0.3	beta (1.5, 3.6, 1)	31
fraction of beetle tissue in little owl diet	$Fr_{4,8}$	unitless	0.1	beta (1.5, 13.25, 1)	31
fraction of vole tissue in little owl diet	$Fr_{6,8}$	unitless	0.29	beta (1.5, 3.7, 1)	31
fraction of shrew tissue in little owl diet	$Fr_{6,8}$	unitless	0.29	beta (1.5, 3.7, 1)	31
existence metabolic rate	EMR	kJ/day	1.45	log-normal (1.5, 0.57)	16
field metabolic rate	FMR	kJ/day	3.57	log-normal (3.6, 0.97)	16
caloric content of earthworms	CC_3	kJ/g food	3.0	log-normal (3.0, 0.6)	16
caloric content of beetles	CC_4	kJ/g food	7.2	log-normal (7.2, 1.6)	16
caloric content of mammals	CC_{6+7}	kJ/g food	7.1	log-normal (7.1, 1.1)	16
caloric content of laboratory diet	CC_lab	kJ/g food	13.7	log-normal (13.7, 2.8)	16
food assimilation efficiency of earthworms	FAE_3	unitless	0.73	log-normal (0.73, 0.1)	16
food assimilation efficiency of beetles	FAE_4	unitless	0.67	log-normal (0.67, 0.1)	16
food assimilation efficiency of mammals	FAE_{6+7}	unitless	0.75	log-normal (0.75, 0.07)	16
food assimilation efficiency of laboratory diet	FAE_lab	unitless	0.73	log-normal (0.7, 0.1)	16

[a] The following conventions for the receptor index (i) were used: 1 = soil, 2 = plant, 3 = earthworm, 4 = beetle, 5 = spider, 6 = field vole, 7 = common shrew, 8 = little owl. [b] For the distribution parameters the following conventions were used: normal (arithmetic mean, arithmetic standard deviation); log-normal (arithmetic mean, arithmetic standard deviation); beta (alpha, beta, scale). [c] Source: Wijnhoven (Radboud University Nijmegen, unpublished data).

TABLE 2. Regression Coefficients for Cd Concentrations in Invertebrates and the Kidney and Liver of Small Mammals

	regression equation				
group	*n*	log *a*	b	r^2	source
beetle	50	−0.051	0.599	0.45	32
spider	61	0.888	0.47	0.37	32
earthworm	33	1.375	0.245	0.33	33
shrew kidney	10	1.427	0.665	0.50	34
shrew liver	10	1.393	0.872	0.52	34
vole kidney	12	0.955	0.927	0.33	34
vole liver	12	0.518	0.945	0.38	34

for the small mammals was calculated as

$$D_i = \frac{\sum_{j=1}^{h} Fn_{ij} \times (\mathrm{IR}_i \times \mathrm{Ct}_{ij})}{W_i} \tag{4}$$

where h is total number of intake items considered (unitless), Fn_{ij} is the normalized dietary fraction of intake item j in the diet of receptor i (unitless), IR_i is the total intake rate of receptor i (g of dry weight/day), Ct_{ij} is the Cd concentration in intake item j of receptor i (mg/kg of dry weight tissue), and W_i is the body weight of receptor i (g).

Regression equations for the residue Cd concentration in kidney and liver of the field vole and common shrew (Cr_{ik} in mg/kg of dry weight tissue) in relation to the daily estimated Cd intake were calculated using

$$\log(\mathrm{Cr}_{ik}) = \log a + b \times \log(D_i) \tag{5}$$

where a and b are the regression coefficients and k is the organ index (I = liver, II = kidney). The regression coefficients for the relations are presented in Table 2. The whole body Cd concentrations for the field vole and common shrew (Ct_i in mg/kg of dry weight tissue) were calculated as follows:

$$\mathrm{Ct}_i = \frac{1}{\mathrm{Fb}_i} \times \sum_{k=\mathrm{I}}^{\mathrm{II}} \mathrm{Fe}_{ik} \times \mathrm{Cr}_{ik} \tag{6}$$

where Fb is fraction of the total Cd body burden concentrated in kidney and liver (unitless) (*27*) and Fe is the weight fraction of kidney and liver to the total body weight (unitless). Finally,

TABLE 3. Distribution Characteristics of the Cd Concentration (mg/kg) for Homogeneous Units Identified within the Afferdensche and Deestsche Waarden Floodplain along the River Waal

unit	description[a]	mean	SD	area (ha)	number of samples
W1B	historic excavation, nonrecent deposition	3.3	2.7	101.0	38
W2A	recent excavation, recent deposition	4.6	2.6	15.1	29
W2B	recent excavation, nonrecent deposition	1.5	1.3	8.6	6
W3A	no excavation, recent deposition	4.5	1.6	5.7	20
W3B1	no excavation, nonrecent deposition, flooding frequency > 20 days/year	2.6	2.3	6.8	3
W3B2	no excavation, nonrecent deposition, flooding frequency < 20 days/year	1.5	0.7	10.2	6

[a] Adapted from ref *40*.

the Cd concentration in the food of the little owl (Cf_8 in mg/kg of wet weight tissue) was calculated using

$$Cf_8 = \sum_{j=1}^{h} \mathrm{Fn}_{ij} \times [\mathrm{Ct}_{ij} \times (1 - P_j)] \tag{7}$$

where P_j is the mean proportion of water in intake item j (unitless).

Toxicity Reference Value. A toxicity reference value (TRV) was used to indicate an exposure level above which the little owl may suffer adverse effects. Because experimental toxicity data on the little owl are lacking, we used toxicity data on other bird species to estimate a TRV for the little owl. No-observed-effect-levels (NOELs) of 11 different laboratory tests with bird species were collected (*26*, *35*), and their median value of 12.2 mg of Cd/kg of wet weight tissue was used as a surrogate NOEL for the little owl. This surrogate NOEL was corrected for differences in toxicity under laboratory and field conditions, using an extrapolation model developed by Traas et al. (*16*) and Luttik et al. (*36*). The model corrects for differences in metabolic rate, caloric content of food, and food assimilation efficiency between laboratory and field animals

$$\mathrm{TRV}_i = \left(\frac{\mathrm{EMR}}{\mathrm{FMR}}\right) \times \left(\frac{\sum_j \mathrm{Fn}_{ij} \times \mathrm{CC}_j}{\mathrm{CC}_{\mathrm{lab}}}\right) \times \left(\frac{\sum_j \mathrm{Fn}_{ij} \times \mathrm{FAE}_j}{\mathrm{FAE}_{\mathrm{lab}}}\right) \times 10^{\frac{1}{n_k}\sum_k \log \mathrm{NOEL}_k} \tag{8}$$

where EMR is the existence metabolic rate, FMR is the field metabolic rate, CC is the food caloric content, and FAE is the food assimilation efficiency (Table 1).

Hazard Index. The potential risk of cadmium to the little owl is represented by a dimensionless hazard index (HI), calculated as

$$\mathrm{HI}_8 = \frac{\mathrm{Cf}_8}{\mathrm{TRV}} \tag{9}$$

The hazard index is not an absolute measure of risk (*28*). It should be interpreted within the context of the assumptions and uncertainties underlying the risk assessment procedure. Here, a hazard index below unity is interpreted as a situation of no immediate concern, whereas a hazard index above unity requires further investigation and, possibly, risk reduction measures.

Uncertainty in Spatial Models. The choice of a model to represent spatial variability within ecological risk assessment can have an important influence on risk outcomes (*8*). Spatial operations, such as interpolation within GIS, contain assumptions and uncertainties that may lead to uncertainty regarding the validity of the model predictions for the real world situation (*9*). In this study, the influence of two spatial model components was evaluated: the choice of the interpolation method and the choice of foraging range dimensions.

Spatial interpolation methods are used to convert concentration measurements at a limited set of sampling locations into continuous concentration maps. There is a wide variety of interpolation methods, each with their own characteristics and underlying assumptions (*20*). The case study includes two interpolation methods that are commonly used in riverine environments and that differ fundamentally in their underlying assumptions: classification (*37*) and kriging (*38*, *39*). Classification is a global method that uses all available data to provide predictions for the whole area of interest. In contrast, kriging is a geostatistical method that describes spatial variation as a stochastic surface. Both methods not only produce concentration estimates, but also provide an estimate of the uncertainty involved.

Classification assumes that the spatial structure of the variation is determined by externally defined spatial processes (e.g., flooding and extraction of sand and clay) resulting in a limited set of more or less homogeneously contaminated units. It is furthermore assumed that most important changes take place at boundaries and that within unit variation is smaller than that between units (*20*). The division into homogeneous units was based on an earlier study (*40*). The Afferdensche and Deestsche Waarden flood plain was divided into six homogeneous units based on location and age of excavations, age of deposition, and flooding frequency (Table 3). The contamination level of the individual units was characterized by combining the available set of sampling points (Figure 2) with the distribution of homogeneous units within the Afferdensche and Deestsche Waarden flood plain (Figure 3).

The theory behind kriging assumes that the variance of a soil parameter at two points in an area increases with increasing distance between those points, while it is independent of the position of the point pair. A measure indicating the amount of variation at two locations separated by a certain lag distance h is the semivariance $\gamma(h)$ that can be estimated as

$$\hat{\gamma}(h) = \frac{1}{2n}\sum_{i=1}^{n}[z(x_i) - z(x_i + h)]^2 \tag{10}$$

where $z(x_i)$ and $z(x_i + h)$ are the values of the variable of interest, x, at location i, and a location lag distance h away, and n is the number of pairs of sample points separated by distance h (*41*). To model the spatial variability of the soil Cd concentration within the Afferdensche and Deestsche Waarden the lag distance h was set at 50 m. A spherical model was fitted through the experimental variogram, based on weighted least squares, and assuming isotropy (i.e., no gradients in a specific direction were expected). This resulted in a nugget value of 0.23, a sill value of 0.78, and a range of 550 m. Finally, the modeled variogram was used to create Cd prediction maps for the total flood plain using ordinary point

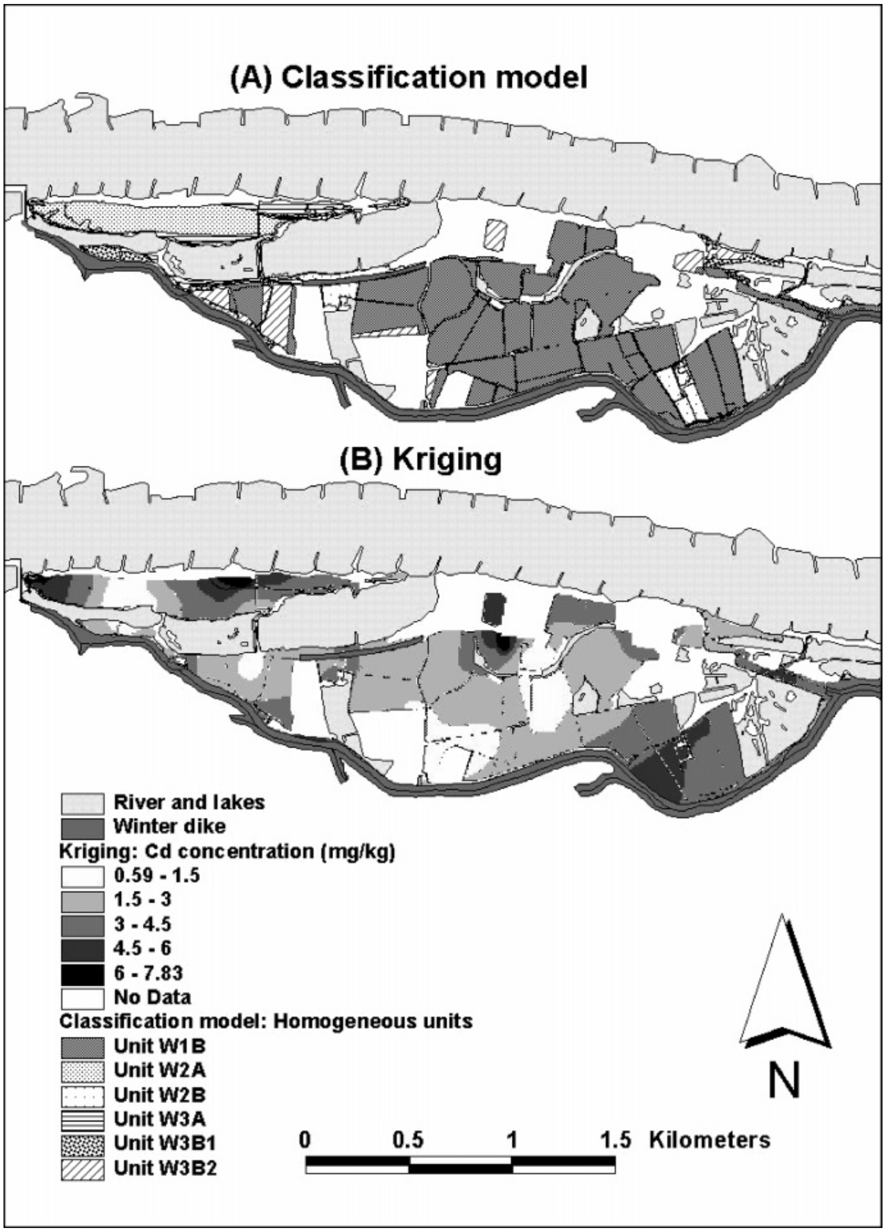

FIGURE 3. Contamination maps for the soil Cd concentration in the Afferdensche and Deestsche Waarden flood plain based on (A) classification and (B) kriging. The distribution characteristics of the Cd concentration in the classification units are described in Table 3. Only the areas within the habitat of the little owl are shown.

kriging (*20*). Modeling of the variogram and kriging was carried out using Gstat software (*42*).

To investigate the influence of foraging range dimensions on the hazard index estimates, calculations were made with a minimum and maximum foraging range observed in field studies for the little owl in river flood plains, i.e., a radius of 90 and 200 m (*31*).

Parameter Uncertainty. A common problem for site-specific ecological risk assessments is the limited data availability resulting in uncertainty about the true value of the parameters within the model. Monte Carlo simulation is a technique to quantify the impact of parameter uncertainty (*43*). It propagates known parameter uncertainties into an uncertainty distribution of the output variable. To perform Monte Carlo simulation, each uncertain input parameter is specified as a distribution. In this study, three main sources of parameter uncertainty were included: (1) uncertainty in soil Cd concentration; (2) uncertainty in the parameters of the exposure model; and (3) uncertainty in the parameters of the effect model.

A normal distribution was used to describe the uncertainty of the area-weighted Cd concentration (Cs_w) for each foraging area. Together with the average Cd concentrations produced by classification and kriging (eq 1), the normal distribution of the weighted Cd concentration per foraging area was characterized by the standard error of the mean:

$$\mathrm{SE}[\mathrm{Cs_w}] = \sqrt{\frac{1}{(\sum_i A_i)^2} \cdot \sum_{i=1}^{n} A_i^2 \cdot \mathrm{SE}^2[\mathrm{Cs}_i]} \qquad (11)$$

where $SE[Cs_i]$ is the standard error of the concentration in unit i within the foraging range circle (mg/kg) and A_i is the area of unit i.

Table 1 shows the distribution parameters describing the uncertainty of both the exposure and the effect model. It was assumed that parameters with a positively skewed distribution in the positive value domain are best represented by a log-normal uncertainty distribution. This distribution avoids negative values, it captures a large value range, and reflects the multiplicative relationships underlying many natural processes and parameters (*44*, *45*). For the proportions of water in tissue, normal distributions were chosen to represent uncertainty (*26*). Dietary fractions can vary between individuals, seasons, habitats, and foraging areas. Beta distributions were selected to model the variation in dietary fraction (*28*). To prevent the sum of F_{ij} for all dietary items for a given consumer from exceeding 1 during any iteration of the model, the individual F_{ij} values were normalized relative to their sum.

The uncertainty in the regression equations that estimate accumulation in invertebrates and small mammals (Table 2) was also evaluated. According to Mendenhall and Beaver (*46*), the confidence interval for the expected value of Y can be described as follows:

$$Y_i = \hat{Y}_i + t_{n-2,i} \cdot s_{\hat{y},i} \tag{12}$$

where $\hat{Y}$ is the expected value for the dependent regression parameter Y, t_{n-2} is central Student t-distribution with $n-2$ degrees of freedom (where n is the number of measurements and 2 refers to the number of parameters of the fitted regression line), and $s_{\hat{y}}$ is the standard error of the mean for $\hat{Y}$.

Simulation. The potential risk for the little owl was evaluated for four different scenarios. Each scenario represents a unique combination of one of the two interpolation methods (classification and kriging) and one of the two foraging ranges (90 and 200 m). In each scenario, a separate Monte Carlo simulation run was performed for each of the 107 potential foraging areas within the study area. The distributions for the hazard indices of these foraging areas were compared with (1) a hazard index distribution that was calculated using the mean Cd concentration distribution for the whole flood plain (i.e., a normal distribution with mean and standard deviation taken from total dataset of 102 samples), and (2) a deterministic hazard index that was calculated using point estimates for all parameters (Table 1). To identify the parameters that contribute most to the output uncertainty, a sensitivity analysis (e.g., Monte Carlo simulation in combination with Spearman Rank correlation) was performed for the little owl hazard index.

Analogous to Slob (*45*), a dispersion factor (DF) is used here as a quantitative measure for spatial variability and parameter uncertainty. This dispersion factor provides a convenient way to quantify uncertainty, and it surpasses other measures of uncertainty (e.g., the coefficient of variation or the variance) with respect to interpretability. The dispersion factor is defined as the ratio between the 95th and 5th percentile value. The dispersion factor for spatial variability (DF_{var}) is defined as the ratio between the 95th and 5th percentile curves. It was calculated at two different probability levels: 5% and 95%.

Monte Carlo simulations and sensitivity analyses were performed in Crystal Ball 5.0 (*47*). Each simulation consisted of 10 000 iterations, resulting in a representative picture of the uncertainty distribution of the hazard index.

Results

Figure 3 shows the two Cd contamination maps that were derived for the Afferdensche and Deestsche Waarden flood plain after interpolation using classification and kriging. Classification results in delineation of homogeneous areas with abrupt transitions between units. Table 3 shows that high contamination levels, especially for the units W2A and W3A along the river, are mainly related to recent deposition of polluted sediments. The kriged map shows a continuous surface with Cd concentrations ranging from 0.7 to 7.8 mg/kg.

Figures 4 and 5 show the cumulative probability functions of the hazard index for the little owl for the four scenarios evaluated. The curves that represent the 5th, 50th, and 95th percentile hazard index distributions for the total set of 107 evaluated foraging areas in the study area are shown for each scenario. The deterministic estimate for the hazard index was 0.9 and is shown as a vertical dashed line. The hazard index that was calculated using the mean Cd concentration distribution for the whole flood plain is shown as a bold line in Figures 4 and 5. It resulted in a mean (± 1 standard deviation) hazard index of 1.4 ± 1.0, with a 5th to 95th percentile range of 0.4 to 3.2. Except for the lower and upper tail of the hazard index distributions the trends for the mean Cd curve and the 50th percentile curve are comparable.

The 5th, 50th, and 95th percentile distributions in Figures 4 and 5 can be interpreted as representing foraging areas with relatively low risk (5th percentile), median risk (50th percentile), and high risk (95th percentile). The difference between these hazard index distributions reflects the impact of spatial variation on the hazard index. The difference in hazard index along the individual probability distributions reflects parameter uncertainty. For example, it can be deduced from the 5th percentile distribution in Figure 4A that there is a 50% probability that the hazard index is 0.9 or less in 5% of the foraging areas. The calculated values of DF_{var} are comparable for all four scenarios and range between 1.4 and 1.6. The dispersion factor for parameter uncertainty (DF_{unc}) is defined as the ratio between the 95% and 5% probability levels of the individual hazard index distributions. It was calculated for the 5th and 95th percentile distributions. The calculated values of DF_{unc} are comparable for all four scenarios and range between 6.4 and 6.7. The large values of DF_{unc} compared to DF_{var} indicate that the overall uncertainty in the hazard index of the little owl is dominated by parameter uncertainty.

The influence of spatial model uncertainty can be evaluated by comparing the plots of the four evaluated scenarios. The uncertainty range of the scenarios is comparable, except for the scenario based on kriging and a 90 m foraging range (Figure 5A), which has a slightly larger range of variation between the 5th and 95th percentile curves. This can be explained by the fact that kriging allows a more detailed characterization of local spatial variability compared to global interpolation methods such as classification (*20*) (Figure 3), resulting in more pronounced differences between foraging areas, especially at small foraging ranges.

Table 4 shows the results of the sensitivity analysis for the foraging areas with lowest and highest area-weighted Cd concentration for the scenario based on kriging and a 90 m foraging range. The results for the mean Cd concentration distribution of the flood plain are also shown. Most of the variation in the hazard index was driven by a small group of parameters of the effect model, i.e., existence metabolic rate, field metabolic rate, and caloric content of laboratory food. Soil Cd concentration contributes considerably (23%) to the variation in hazard index based on the mean Cd distribution of the flood plain. However, the contribution of the soil Cd concentration is only minimal for the two foraging areas with low and high Cd concentrations.

Discussion

Methodology. The methodology presented in this paper offers the opportunity to compare different sources of variability and uncertainty in ecological risk assessment. The coupling of GIS and probabilistic exposure and effect models make it possible to include and investigate interactions between the spatial distribution of habitat area, foraging area,

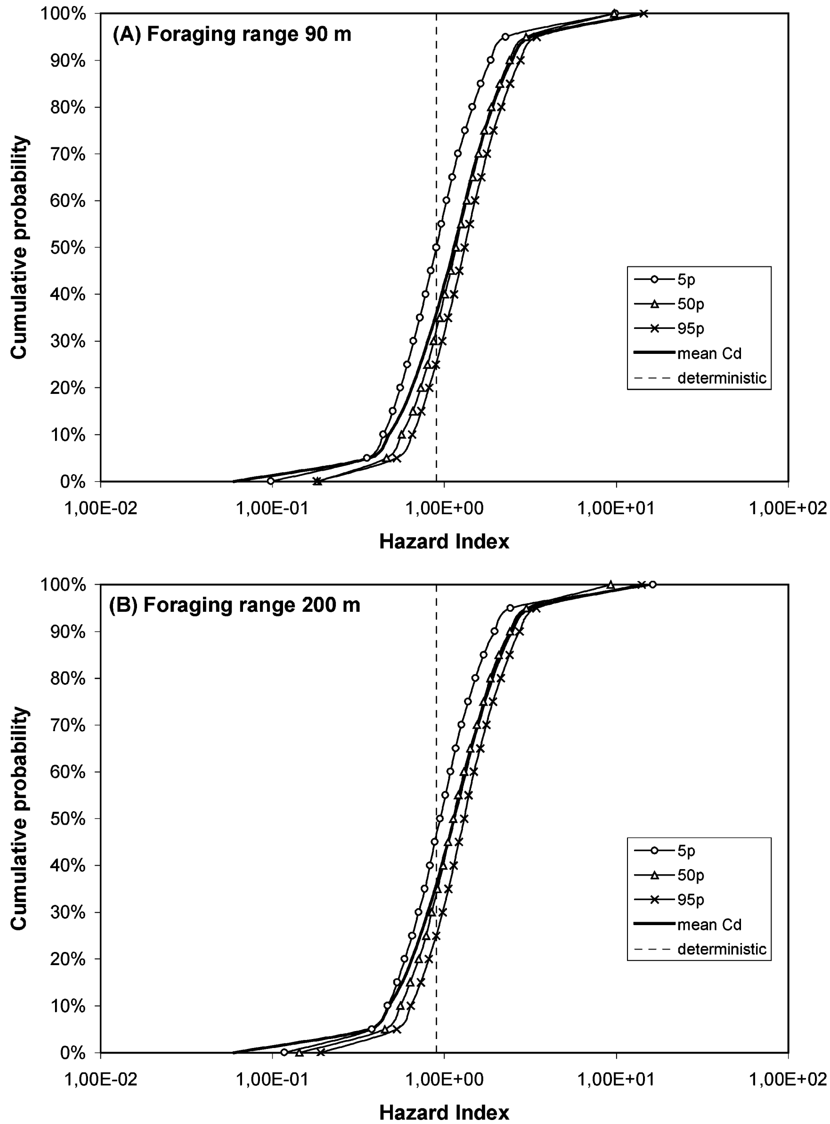

FIGURE 4. Cumulative probability functions of the hazard index for the little owl exposed to Cd within the Afferdensche and Deestsche Waarden flood plain using classification as interpolation method with foraging ranges of (A) 90 m and (B) 200 m. The 5th, 50th, and 95th percentile distributions (5p, 50p, and 95p) of the total set of 107 foraging ranges evaluated are shown, as well as the distribution for the mean Cd distribution of the whole flood plain (mean Cd) and the deterministic estimate for the hazard index of 0.9 (deterministic).

contamination, and exposure. The methodology was evaluated in a case study on the potential risks of cadmium for the little owl in a Dutch river flood plain, revealing the impact of spatial patterns in Cd contamination and habitats. In addition to the procedure described by Kooistra et al. (*12*), the current study takes spatial variability of habitat suitability for prey of the little owl into account, and the exposure and effect model was updated with recent food web relations. Although the methodology was applied for the specific situation of metal contaminated flood plains, it can also be applied to other areas, endpoint species, or contaminants. The methodology can be an useful instrument to set priorities in environmental management, e.g., for the identification of areas that require further investigation or remediation.

Case Study. Figures 4 and 5 show that the Cd pollution in the Afferdensche and Deestsche Waarden results in a hazard index for the little owl that ranges between approximately 0.1 and 10. The deterministic estimate of the hazard index is 0.9, but this value provides no information on the range of risks that might be expected. Using the mean Cd concentration distribution for the whole flood plain results in a median hazard index of 1.2, while the probability of a hazard index > 1 is 57%, and for a hazard index > 10 is 2%. The median hazard index of the 5th and 95th percentile distributions of the 107 evaluated foraging areas varies between 0.8 and 1.4, while the probability of a hazard index > 1 varies between 35 and 73%. These results indicate that any single estimator may over- or underestimate risk, depending on parameter uncertainty, foraging strategy, interpolation method, and spatial patterns in habitat and contamination.

In an earlier study in the Afferdensche and Deestsche Waarden by Kooistra et al. (*12*), the probability of a hazard index > 1 varied between 23 and 35%, which is considerably lower than in the present study. This can mainly be contributed to the fact that in the earlier study it was assumed that the foraging area of the little owl consisted of the whole flood plain area, including the high-water free areas of former brick factories with relatively low Cd contamination levels. However, these areas are beyond the assumed habitat for small mammals and thus were not included as foraging area for the little owl in the current study. This comparison shows that the spatial distribution of habitat and foraging area directly affects the potential risk.

Studies to validate model results for the little owl are scarce. A field study in a flood plain along the river Rhine

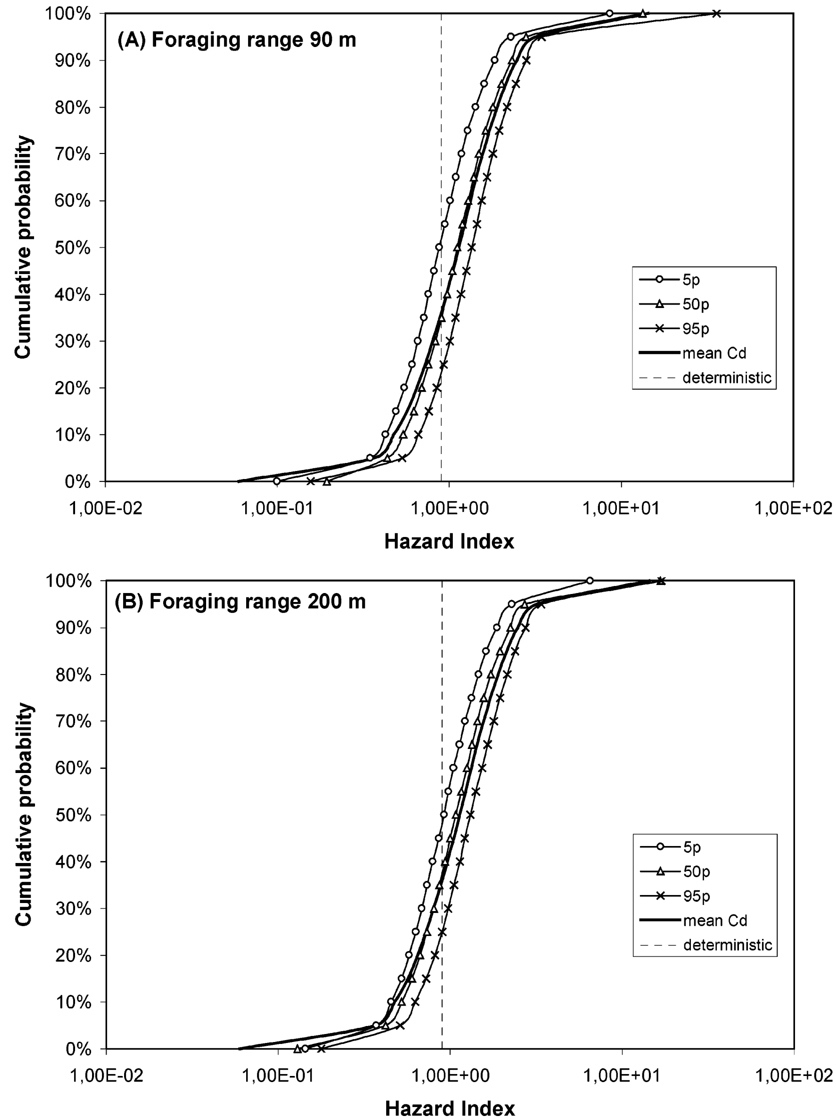

FIGURE 5. Cumulative probability functions of the hazard index for the little owl exposed to Cd within the Afferdensche and Deestsche Waarden flood plain using kriging as interpolation method with foraging ranges of (A) 90 m and (B) 200 m. The 5th, 50th, and 95th percentile distributions (5p, 50p, and 95p) of the total set of 107 foraging ranges evaluated are shown, as well as the distribution for the mean Cd distribution of the whole flood plain (mean Cd) and the deterministic estimate for the hazard index of 0.9 (deterministic).

TABLE 4. Ranking of the Parameters of the Exposure and Effect Model According to Their Contribution to the Variance in the Little Owl Hazard Index Estimates[a]

parameter	symbol	contribution to changes in little owl hazard index (%) low Cd conc	high Cd conc	mean Cd conc
existence metabolic rate	EMR	45.9	46.0	33.2
soil Cd concentration	Cs_w	0.4	0.0	23.0
field metabolic rate	FMR	22.3	22.1	15.6
caloric content of laboratory diet	CC_lab	11.8	11.8	11.3
central Student t-distribution for regression Cd concentration in liver shrew	$t_{n-2,7,l}$	5.4	4.4	4.1
food assimilation efficiency of laboratory diet	FAE_lab	4.7	4.7	4.9
caloric content of earthworms	CC_3	2.0	2.5	2.0
total		**92.5**	**91.5**	**94.1**

[a] Results are presented for the foraging areas with lowest and highest Cd concentration based on the kriged contamination map and a foraging range of 90 m, and for the mean Cd concentration distribution of the whole flood plain (mean Cd).

(*17*), with soil Cd concentrations ranging from 1.4 to 2.7 mg/kg, concludes that effects of heavy metals in little owls are not likely to occur. However, if only earthworms are available for foraging owls, cadmium exposure may result in adverse effects. The soil Cd concentrations reported in the current study are considerably higher in some areas, resulting in estimated exposure concentrations above the TRV. The results of the case study do not allow conclusions on the prevalence of adverse effects of cadmium for the little owl. However, the fact that the hazard index exceeds unity in some areas indicates a possibility of adverse effects that should be investigated further, e.g., by performing field measurements.

The wide ranges of the probability distributions in Figures 4 and 5 (reflected in the relatively large values of DF_{unc}) indicate that parameter uncertainty dominates the overall uncertainty in the estimated hazard index of the little owl. The results of the sensitivity analysis (Table 4) show that this variation is mainly caused by the parameters of the effect model (i.e., EMR, FMR, CC_lab, FAE_lab). A large impact of effect parameters on risk estimates was also observed in other studies (*14*, *16*). An important reason is the limited availability of species- and site-specific ecological and toxicological information, resulting in the use of more general and uncertain input parameters. Therefore, to reduce overall uncertainty in ecological risk assessment, more reliable data on species- and site-specific effect parameters are required.

The results in Figures 4 and 5 indicate that the impact of spatial factors (i.e., spatial variability in contaminants and habitats, and spatial model uncertainty) on the overall uncertainty in the hazard index is of minor importance when compared to parameter uncertainty. However, several factors should be considered before general conclusions can be drawn. First, the case study results strongly depend on the case study settings. If these settings change (e.g., spatial distribution and levels of contamination, change in food web), the outcome, including the importance of the different types of variability and uncertainty, might change. For example, some areas within contaminated flood plains along the river Waal consist of highly contaminated material with Cd concentrations > 12 mg/kg. Several studies (*7*, *12*) have shown that contamination hotspots can have a significant impact on species with a small foraging range resulting in high site-specific risk levels. Additional research is required to assess the effect of extreme contamination levels and different spatial patterns in other flood plains on risk estimates.

Second, the spatial models used here do not include all spatial factors that may influence risk. For example, the spatial distribution of organic matter content of soil, pH, and other factors that may influence bioavailability of metals, and thus exposure, were not included. Furthermore, the model assumes that all receptors forage evenly within the suitable habitat of a foraging area not directly accounting for habitat quality, patchiness, and connectivity. Individual behavior of the receptors (prey and predators), as determined by individual food preferences, genetic background, and typical habits, was not included. Both for the little owl and the small mammals, random movement models that generate spatially explicit individual and population exposure estimates for terrestrial receptors could be adopted for a more realistic simulation of animal movement (*6*, *7*). Finally, temporal components that were not explicitly included in our approach can have an important influence on exposure for species in riverine ecosystems. For example, flooding of the flood plain during spring results in a change of the feeding fractions for the little owl (e.g., from small mammals to earthworms), while foraging areas are temporary displaced outside the flood plain (*22*).

Finally, it should be realized that uncertainty is a reducible quantity, whereas spatial variability is a physical phenomenon that cannot be reduced (*14*). Over time, uncertainty in risk estimates is likely to be reduced, but spatial variability remains. It is therefore important that we now expand the approach that is presented in this paper and develop methods and techniques that can describe the impact of spatial variability on ecological risk estimates.

Notwithstanding the limitations of the case study setting and the incomplete inclusion of spatial factors in our model, our case study clearly demonstrates that spatial factors can have a significant impact on the hazard index of the little owl. The differences between the foraging areas are clearly observable in Figures 4 and 5 by comparing the 5th, 50th, and 95th percentile distributions. Potential risks calculated for individual foraging areas show a reduced contribution of the soil Cd concentration compared to the overall uncertainty for the whole flood plain (Table 4). This is caused by the fact that relatively high exposures within a foraging area are outbalanced by lower exposures. This "smoothing effect" depends on size of the foraging range and it explains why the range between the 5th and 95th percentile distributions in Figures 4 and 5 are slightly wider for a 90 m foraging range than for the 200 m ranges.

The differences between the two evaluated interpolation methods are relatively small. This is in line with the results of other studies that compared different interpolation methods (*48*). Since kriging requires a large set of costly soil samples to estimate a reliable semivariogram, it is more cost-effective to base future risk assessments in other flood plains on generally available soil quality maps derived using classification models.

Results from a probabilistic approach in ecological risk assessment will on one hand provide flood plain managers greater insight into the consequences of uncertainty and variability inherent in the data and modeling approach. On the other hand decision-making based on these results is not straightforward and careful interpretation and communication are required (*28*). Further application in environmental management therefore requires a general framework for risk management that includes both uncertainty and spatial components. On the basis of this framework current risks and those for planned future reconstruction measures in the river flood plains along the rivers Rhine and Meuse can be evaluated.

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