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Exposure and Exposure Modeling

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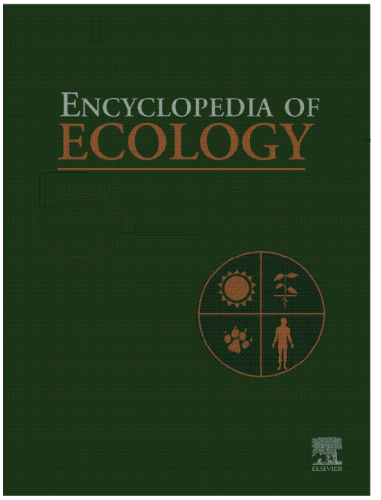
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hunting, fishing, and forestry, humans have transformed most ecosystems on land, freshwater, and in the sea. To date exploitation of wild living resources continues to be one of the dominating drivers of ecological change worldwide. Exploitation affects population by increasing mortality, and by relaxing intraspecific competition. The resulting increase in net growth can be the basis for sustainable exploitation. Unsustainable exploitation, however, has been the norm throughout history and has led to the depletion and extinction of a large number of species. Exploitation often progressed from large, long-lived species to smaller, short-lived ones, and can lead to large changes in size and age structure both within and between species. The indirect ecosystem effects of exploitation include trophic cascades and other alteration of species interactions, as well as habitat effects. Exploitation has been shown to interact strongly with other ecological factors, mainly productivity, disturbance, and climate. These factors and exploitation can therefore not be assessed independent of one another. Restraining exploitation on a global scale and recovering overexploited resources remains one of the central challenges of humanity.

See also: Community; Predation.

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Exposure and Exposure Assessment

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Trophic Transfer and Exposure Estimates
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Introduction

Exposure to contaminants in the environment is quantified through the ecological risk assessment (ERA) process which provides a framework for the development and implementation of environmental management decisions. The ERA uses available toxicological and ecological information to estimate the probability of occurrence for a specified undesired ecological event or endpoint. The level for these endpoints depends on the objectives and the constraints imposed upon the risk assessment process; therefore, multiple endpoints at different scales may be necessary. ERAs

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often rely on the link between these undesired endpoints to a threshold of exposure to specific toxicants and toxicant mixtures. Oral reference doses (RfD), inhalation reference concentrations (RfC), and carcinogenicity assessments are the usual way these links are expressed in the ERA, and unfortunately most of these thresholds have been developed for human health assessments and not ecosystem integrity. However, since these studies often use animal models, in many cases the original empirical data can be used when trying to apply these findings to ecological consequences or to establish ecological screening values (ESVs). The ecological exposure assessment often begins by comparing constituent concentrations in media (surface water, sediment, soil) to ESVs. The ESVs are derived from ecologically relevant criteria and standards. For example, in the United States the United States Environmental Protection Agency (USEPA) Screening Values and National Ambient Water Quality Criteria (NAWQC) are often used based on 'no observed adverse effect levels' (NOAELs) or 'lowest observed adverse effect levels' (LOAELs) derived from literature to assess exposure. Radionuclide comparisons for ecological screening are typically dose-based for population level effects. In addition to the ecological threshold comparison, constituents that may bioaccumulate/bioconcentrate are identified during initial screening processes. This is done to account for toxicants that may not be present at levels exceeding ESVs, but must be considered due to trophic transfer of toxicants that may concentrate in higher-trophic-level organisms. Constituents that exceed ESV comparisons (present with means, maximums, or 95% upper confidence levels (UCLs)) are evaluated using a lines-of-evidence approach based on (1) a background evaluation, (2) a bioaccumulation/bioconcentration potential and ecotoxicity evaluation, (3) a frequency and pattern-of-exceedances evaluation based on review of exceedances to the ESVs, and (4) an evaluation of existing biological data. From this information, ecosystems can be prioritized in terms of risk and focused for proper exposure assessments. This article presents a scientific overview and review of how toxicant exposure is estimated and applied to assess ecosystem integrity.

Estimating Toxicant Exposure

The challenge in estimating exposure to toxicants is to properly model ecosystem function. Exposure modeling must consider a hierarchical scale, system dynamics, and use them to determine what the limits of predictability may be. A hierarchical approach allows modelers to characterize exposure components and their linkages among different scales of ecological organization and complexity. Therefore, exposure needs to be analyzed at multiple scales and appropriate levels of ecological organization in both space and time. Although estimating exposure in terrestrial and aquatic ecosystems is linked, there are special considerations that need to be taken for each.

Aquatic systems are considered primary integrators within a watershed because they potentially receive, through surface or subsurface drainage/discharge, toxicants from outfalls and other contaminant sources within the watershed. If these toxicants reach biologically significant levels, they would be expected to affect the numbers, types, and health of stream organisms. Often, biological sampling is conducted in a stream system to measure the cumulative ecological effects of contaminant sources received by the aquatic system (pond, stream system, lake, etc.). Information from biological sampling is used to assess the environmental quality based on contaminant exposure and is often termed bioassessment. For aquatic assessments, evaluation areas are partitioned spatially, based on watershed boundaries and potential contaminant sources and classified in terms of the type of surface water body (streams, lakes, etc.) and their associated wetlands, including surface water, sediment, and related biota. These systems receive potential contamination discharged to surface water or migrating through groundwater from source contaminant areas, National Pollutant Discharge Elimination System outfalls, and operational facilities to points of potential receptor exposure. Ecological receptors feeding within stream-based food chains are exposed to the cumulative effects of contaminants that are released to the stream system, and their health can be considered an integrative indicator of the severity of contamination within the watershed. Because some watersheds/stream systems are large in size, the study area may need to be subdivided into subunits to facilitate the assessment process and identify areas of possible contamination with higher precision.

Exposure assessment models have primarily focused on the mobility of contaminants in the environment using vertebrates as the assessment endpoint (e.g., exposure to each contaminant in $\mathrm{mg\,kg^{-1}\,d^{-1}}$ or $\mathrm{mg\,l^{-1}\,d^{-1}}$). Invertebrate models are also used especially when soil screening levels (SSLs) are of interest; however, these studies usually concentrate on transfer factors associated with bioaccumulation models. As mentioned previously, the affects assessment may be expanded beyond comparison to ESVs by using existing data to conduct trophic exposure modeling (hereafter trophic modeling). Trophic modeling can be used to refine the list of toxicants to those constituents that may pose an adverse impact (significant risk) to specific ecological receptors. The trophic modeling uses toxicant exposure models for ecological receptors to calculate an exposure dose (ED) for each constituent that poses a potential risk through ingestion of contaminated media. EDs are compared with toxicity reference values (TRVs) to identify constituents with an evaluation-level hazard quotient (HQ, i.e., ED/TRV)

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greater than 1. Results of the HQ assessment and other weight-of-evidence criterion can be used to further refine the list of constituents of potential concern. The use of exposure assessments must be appropriate to the spatial scale across which the toxicants of interest are dispersed. The most influential factor for contaminant accumulation in wildlife in any ecosystem is how much time the individual spends exposed to the contaminant and how it utilizes the ecosystem. In areas with broad-scale contamination, this must be done at the landscape level and can be achieved by the implementation of spatially explicit models that are calibrated using data from long-term biomonitoring of large areas. Specifically, exposure assessment considers the following:

1. Chemical distribution which defines the extent of measured chemical contamination to each exposure area and the approximate acreage of each exposure group. The chemical exposures that may be experienced by ecological receptors are affected by the degree of their spatial and temporal associations with the contaminated media.

2. Receptor distribution which involves the variety of factors that may affect the extent and significance of potential exposures. Receptor exposures are affected by the degree of spatial and temporal association with the contamination. A receptors' mobility may significantly affect their potential exposures to contaminants. Many species may only inhabit the study area during the seasonal periods (e.g., breeding season, nonmigratory periods). Nonmigratory species may remain in the vicinity throughout the year. These species, particularly those with longer life spans, have the greatest potential duration of exposure. For both terrestrial and aquatic systems, some species may live their entire life cycle within the systems and others may utilize the system for forage areas, water intake, reproduction, or utilize the area for early life stages only.

3. Quantification of exposure and effects assessment defines the degree to which contaminant distributions and receptor distributions overlap and indicates which receptors are likely to have the greatest potential exposures to contaminants. This can be conducted by comparing media concentrations to ESVs or further quantify exposures by calculating an intake for each chemical in each medium (sediment, surface water, prey). The effects assessment defines and evaluates the potential ecological response to the contaminant by use of TRVs or ESVs that are the basis of the comparison. To relate these numeric comparisons to the actual receptors, biological data can be used to determine if effects are occurring in the system.

As fish and wildlife occupy different habitats within an ecosystem, they may be exposed to toxicants through three pathways: oral, dermal, and inhalation. Oral exposure occurs through the consumption of contaminants through food, water, or soil/sediment. Dermal exposure takes place when contaminants are absorbed directly through the skin. Inhalation exposure occurs when volatile compounds or fine particles are respirated to the lungs. Therefore, the total exposure experienced by an individual is the sum of exposure from all three pathways or

$$E_{\text{total}} = E_{\text{oral}} + E_{\text{dermal}} + E_{\text{inhalation}} \quad [1]$$

where E_{total} is the total exposure from all pathways; E_{oral} is the oral exposure; E_{dermal} is the dermal exposure; and $E_{\text{inhalation}}$ is the exposure through inhalation.

In aquatic systems exposure via inhalation and dermal pathways are usually considered as one factor. This is because total uptake for free-swimming aquatic receptors is assumed to be represented by simple partitioning from surface water alone. Aquatic receptors are assumed to be in equilibrium with contaminants in the water column (this assumption in many cases is erroneous and warrants further research). Contaminant partitioning between surface water and aquatic organisms is defined by a contaminant-specific bioconcentration factor. In general, the primary mechanism of contaminant uptake for many fully aquatic species is via direct uptake across permeable membranes such as gill and gill structures (which can be addressed under dermal exposure in eqn [1]). This can occur as a passive transfer or an active biological process (osmoregulation). Prey consumption, incidental ingestion of sediment and pore water/groundwater during prey consumption, and incidental ingestion of surface water during prey consumption are usually treated as secondary uptake mechanisms since they are modeled via bioconcentration factors rather than exposure models. This potential exposure parameter should be considered spatially dynamic since contaminant concentrations change based on their distance from a source.

Dermal exposure is assumed to be negligible for birds and mammals on many hazardous waste sites relative to other routes in most cases. Feathers and fur of birds and mammals further reduce the likelihood of significant dermal exposure by limiting the contact of skin with contaminated media. However, when an exposure scenario for a receptor species is likely to result in significant dermal exposure such as through brood patches on birds, direct contact by burrowing mammals, or swimming by amphibians, this exposure pathway should be estimated using models for terrestrial wildlife listed in the 'Further reading' section. Moreover, if contaminants that have a high affinity for dermal uptake are present (e.g., organic solvents and pesticides), dermal pathways should be considered even if contact is minimal compared to the aforementioned taxa. Inhalation of contaminants is treated as negligible at many waste sites since quite often these sites are either capped or vegetated. This minimizes exposure of contaminated surface soils to winds which

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results in aerial suspension of contaminated dust particulates. Also, the contaminants most likely to present a risk through inhalation exposure, such as most volatile organic compounds (VOCs), will quickly volatilize from soil and surface water to air, where they are diluted and dispersed. As a result, significant exposure to VOCs through inhalation is unlikely. In circumstances where inhalation exposure of endpoint species is believed to be occurring or is expected to occur, models for vapor or particulate inhalation may be employed.

Based on these factors, most exposure models in fish and wildlife concentrate on exposure through ingestion. The general formulas used to estimate contaminant exposure to terrestrial and aquatic wildlife via ingestion uses the ingestion rate multiplied by the concentration of the contaminant in all possible food items in relation to the body weight of the animal. Because many waste sites (contaminated areas) do not provide suitable habitats, exposure estimates are modified to be sensitive to the home-range size (total area used by an animal) or core area (areas used most often within an animal's home range) of the species as well as the habitats that are used or the probability of the species occurring in the area. These parameters are incorporated in the following equation:

$$E_j = P\left(\frac{A}{\mathrm{HR}}\left[\sum_{i=1}^{m}\left(\frac{\mathrm{IR}_i C_{ij}}{\mathrm{BW}}\right)\right]\right) \qquad [2]$$

where E_j is the exposure to contaminant through ingestion (j) (mg k^{-1}g d^{-1} or mg l^{-1} d^{-1}); P is the probability of the receptor species inhabiting a waste site or the proportion of the waste site used; A is the area (ha) of waste site; HR is the area (ha) that defines the receptor species home range or core area; m is the total number of ingested media (e.g., food, water, or soil); IR_i is the ingestion rate for media (i) (kg d^{-1} or l d^{-1}); C_{ij} is the concentration of contaminant (j) in medium (i) (mg kg^{-1} or mg l^{-1}); and BW is the whole body weight of endpoint species (kg).

The area is considered in two dimensions even for aquatic species since the area-to-home-range ratio is used to determine the fraction of the waste site in relation to the total area used by the animal for foraging. This could of course be modified to a volumetric parameter for aquatic species where the third dimension is necessary to determine that ratio.

Modeling Exposure to Environmental Contaminants

Advances in geographic information science (GIS) technologies such as remote sensing, spatial databases, and spatially explicit models have shown to be extremely useful in the exposure assessment process. By adopting such technologies, landscape-level exposure models can be developed by integrating the spatial parameters such as those shown in eqn [2]. These methods recognize that if a site is spatially heterogeneous with respect to either contamination or animal use, exposure models must be modified to include the dynamics imposed by those spatial factors thus improving the estimated parameters in eqn [2]. When using fish and wildlife as receptor species for mechanisms of contaminant accumulation, transport, redistribution, and as ecological endpoints, the foundations and principles of animal habitat relationships and the interaction between spatial pattern and ecological processes must be properly modeled with particular attention to (1) spatial relationships among fish and wildlife and their habitats, (2) spatial and temporal interactions, and (3) influences of spatial heterogeneity on biotic and abiotic processes. Below, the basic elements needed to estimate the spatially explicit parameters used in most exposure models are outlined.

Data Layers for Exposure Assessment

Through various methods of data capture, such as remote sensing, global positioning system (GPS), and field survey, detailed biophysical characteristics of the landscape can be represented in a GIS. In the form of map layers, a GIS can store the spatial patterns of individual geographic phenomenon, such as habitat, land use, hydrology, population, topography, road networks, and other infrastructural information into a spatial database. The map layers are geographically referenced in a common coordinate system so that the layers are projected onto a scale-down plane surface that enables distance measurement, area calculation, and map overlay.

Historically, the map layers are often too general to make fine-resolution predictions in terms of how receptors may be utilizing contaminated areas or if the map layers were constructed with a focus on timber management and harvest rather than being designed to describe the ecosystem structure. For example, LANDSAT imagery has 30 m spatial resolution (i.e., each pixel has a ground equivalent dimension) and is commonly used for mapping the distribution of vegetation. Recently, the emergence of high-resolution remotely sensed imagery such as QuickBird, airborne visible/infrared imaging spectrometer (AVIRIS), and light detection and ranging (LIDAR) has enabled the researchers to map the three-dimensional information of the landscape with spatial resolution of <1 m and hundreds of spectral channels. Through various techniques of digital image processing, including image filtering, band ratioing, feature/pattern extraction, and spectral classification, biophysical characteristics of the landscape can be extracted from the remotely sensed imagery. The specific technology to be

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used to map out vegetation in the study site is dependent upon the stage of the bioaccumulation model that is being estimated; that is, the scale needed to determine transfer factors from soil to plant species to estimate bioavailability is very different from the scales needed to estimate the distributions of wildlife endpoint species. In many cases, field survey is necessary for verifying, calibrating, and validating purposes.

Once all the map layers are in digital format, the data can be compiled into a spatial database in which many spatial relationships could be explored and analyzed within and among the map layers. To assist risk assessors, the spatial database provides important information about how the focal wildlife species may use contaminated areas and how contaminants may move in the environment. Such a database is extremely useful in identifying potential data gaps and which data sources are available to assist in a risk assessment. In some cases, information on the spatial distribution of contaminants and waste units are not available, and methods of spatial interpolation can be used to generate new information based on known value at surrounding locations (see the following section).

Contaminant Distribution

For most areas it is difficult to map the distribution of contaminants in the soil or sediment. The most notable exception is gamma-ray detection for radioisotopes, which can be achieved through remote-sensing flyovers of the disturbed areas. However, when the contaminants of concern cannot be measured remotely, or the scale of such flyover data is too coarse, some sampling regime has to occur to determine their distribution. Once samples are obtained, contaminant distributions can be mapped using appropriate spatial interpolation techniques.

The first law of geography (Tobler's law) states the likelihood of things closer in distance to be more related and similar than those afar. Built upon this concept, spatial interpolation methods estimate unknown sampling points in relation to the distance of their neighbors near and far. Inverse distance weighting (IDW), local polynomial, global polynomial, spline and radial basis functions (RBSs) are deterministic interpolators that apply an established mathematical formula to the sample points. A second family of interpolation methods consists of geostatistical methods that are based on statistical models that incorporate autocorrelation (statistical relationships among the measured points). Not only do these techniques have the capability of producing prediction surfaces, but they can also provide some measure of the accuracy of these predictions using cross-validation techniques. Kriging is the most widely used geostatistical interpolator. An important feature of geostatistical analysis is the generation of an empirical semivariogram to estimate the spatial correlation of the sampling points in space. Thus, the semivariogram quantifies how the correlation between two points in space changes as they move closer together or farther apart. This is a useful tool in its own right and defines the variance structure of the geostatistical model.

Exposure Model Classification

The development of many spatially explicit exposure models to estimate the adverse impact of specific toxicants and toxicant mixtures to the environment was in part fueled by the demand in understanding the fate of contaminants in terms of environmental risk and environmental justice. In general, an exposure model provides the framework that uses one of the many functions in combining the identified controls (i.e., factors) in assessing the ecological risks. Depending on the basis of the actual algorithms, most of the existing predictive models can be broadly classified as physical-based, statistical-based, and rule-based models. Depending on how the model treats randomness in time and space, the exposure models can further be categorized as deterministic or stochastic models (**Figure 1**). A deterministic model does not

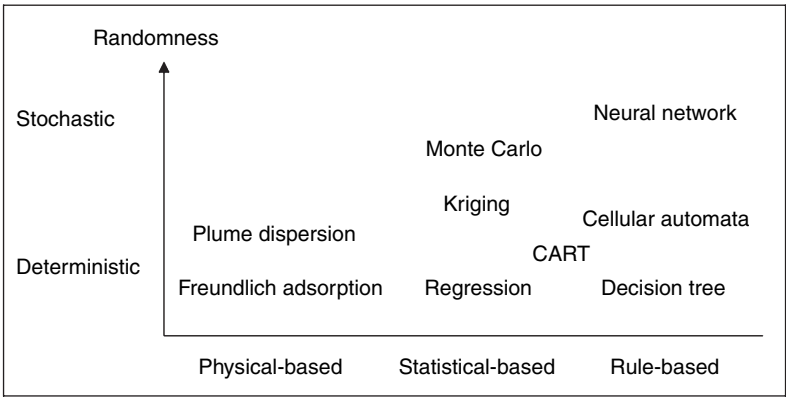


Figure 1 Classification of the spatially explicit exposure models based on the basis of algorithms and randomness.

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consider randomness at all; that is, a given set of input parameters always yield the same output prediction. A stochastic model allows the quantification of uncertainties in time and space, so that the same set of input parameters may have different results. In exposure modeling, uncertainties may come from the lack of input data or understanding about the physical reality, such as seasonality of the ecosystem, random behavior of individuals, etc.

The physical-based models adopt established laws or mathematical equations that attempt to describe the physical processes, for example, Freundlich adsorption equation, toxicokinetic model, plume dispersion model, etc. This type of model is commonly used in modeling the exposure and uptake of toxicants to the endpoints through media such as air, water, and soil. In general, a physical-based model is well established in physical laws and can be extensively applied to many endpoints. However, such models often require many physical parameters that may not be readily available (particularly in spatial data) and the accuracy of model prediction is limited by the extent of field calibration.

The statistical-based models explore the relationship (which can be attribute or spatial in nature) between identified controls and the level of exposure at endpoints with a probability distribution function, for example, generalized linear models, spatial statistical methods, etc. In most cases, this approach is based on empirical data collected from the field or in the laboratory. Many researchers utilized common statistical techniques to conduct ERA, such as logistic regression, kriging, Monte Carlo simulation, etc. The implications of the research that resulted from such models are usually restricted to the tested study areas or ecosystems with similar biophysical characteristics.

The rule-based (or agent-based) models assess the ecological impact of exposure by exploring the underlying mechanisms to simulate the process. The governing rules may be established from the literature or field experts, observed data for both training and validating (e.g., neural network, decision tree), or even arbitary rules (e.g., cellular automata, weighted linear combination). Within this category of model, one of the most controversial components is how to determine the weight of individual controls (i.e., the impacts) in computing the exposure level. The most common weights include the population of receptor species and the space–time interaction between the endpoints and stresses.

Exposure to Populations

When conducting an ecological assessment it is often desirable to estimate the risk to a population rather to an 'at-risk individual'. To model population exposure, one must estimate the proportion of the local population exposed at levels that exceed toxic thresholds. This represents the proportion of the population potentially at risk. Specifically, the proportion of a population potentially at risk is represented by the number of individuals that may use habitat within waste unit(s). To properly estimate exposure, the movement of contaminated individuals within and between populations (metapopulation) may also be of interest especially when the proportion of new recruits is important to estimate the effects of the contaminant on fecundity and survival.

Also, often investigators are interested in making inferences about the mean exposure to a receptor species at a waste site, but it may be erroneous to assume that the distribution of the mean is the same as that of the population. Hence, a similar procedure needs to be performed to estimate the distribution of mean exposure. By estimating the number of individuals (n) that would use the waste site(s), n home ranges for the waste site(s) can be randomly sampled, the n exposures calculated, and the average taken based on eqn [2]. This procedure is repeated (usually 1000+) times for each site creating what is commonly referred to as a Monte Carlo random sample of average exposures. Hence, the resulting simulations provide an estimate of the distribution of mean exposure using histograms and quantiles. The 2.5th and 97.5th elements in the ranked 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). Another approach is to combine the results of Monte Carlo simulation of exposure with literature-derived population density data to evaluate the likelihood and magnitude of population-level effects on wildlife.

Trophic Transfer and Exposure Estimates

Although the concepts of trophic transfer and bioaccumulation are outlined elsewhere, it is worth noting here in the discussion of estimating exposure. The key to a useful exposure model is to derive a realistic link between exposure and uptake. Up to this point this article has focused on the landscape level and behavioral parameters associated with exposure models. However, most exposure models assume that the diets and the proportion of food items that the animal ingests are known. Contaminant exposure is strongly linked to the kind of material an organism occupying lower trophic levels ingest – for example, leaf versus fruit, or

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particular invertebrate species. Contaminant studies have relied on comparisons among a variety of target species, which confound interpretations due to dietary variations and differences in interspecific physiologies. It has been suggested that animals which show a higher diversity of food items better represent the extent of contamination and trophic transfer within a system, especially when they occupy the uppermost trophic levels. For some vertebrates, trophic level rather than body size (which is the usual parameter used) appears to be one of the most important factors.

However, accurately quantifying an animal's diet down to specific food items and quantities is extremely difficult. This is often achieved through fecal and stomach analyses, which are at best snap shots in time and do not capture the animals trophic position over a specified duration (such as weeks to seasons). These difficulties have biased exposure studies to animals with specialized diets, which is extremely unrealistic and may not adequately represent the dynamics of the ecosystem being studied.

One of the most promising techniques available that can minimize some of this variation is through analyzing tissues and food items using stable isotopic analyses. The stable isotope composition of biological materials provides insights into the life histories of fish and wildlife species. It has been demonstrated that animal tissues are enriched in ^{15}N in relation to their diet. Also, owing to differences in photosynthetic pathways, C_3, C_4, and CAM plants have different $^{13}C/^{12}C$ ratios ($-32‰$ to $-22‰$ and $-23‰$ to $-9‰$, respectively, with CAM overlapping) and can be used to identify sources of primary productivity in the diet. The differences in isotopic composition between any tissue compartment of an animal and diet is represented by a tissue–diet enrichment factor $\varepsilon_{\text{tissue–diet}}$, where $\varepsilon_{\text{tissue–diet}} \approx \delta_{\text{tissue}} - \delta_{\text{diet}}$ and 'δ' is the delta value for the isotope of interest. This technique allows researchers to determine what levels of the food chain target species within an ecosystem are occupying and potentially where an animal is foraging. This enables a more sophisticated understanding of food web structure and spatial foraging patterns thus allowing exposure estimates to be better parametrized.

Linking Exposure to Uptake

The biggest challenge to date in exposure modeling is to link exposure to uptake outside of the laboratory. A biomagnification model that was successfully applied to terrestrial biomagnification known as BIOMAG is a good example of linking exposure to uptake. The model considers target species which are top predators in significant ecosystems. The model incorporates a consideration of bioavailability (concentration in soil solution), ecology (stochastic food chain models), toxicology (simple compartment model), and a consideration of effect based on the 'no observed effect concentration' (NOEC). Movement of the contaminant through the food chain is quantified using bioaccumulation factors (BAFs); a ratio of the concentration of contaminant in the consumer and the food that it consumed. Such approaches have been used to underpin soil standards by calculating the level of soil pollution that gives rise to the maximum tolerable risk for birds and mammals at the top of the particular food chain, and in general involves working backward through the model, starting at maximum tolerable risk. One shortfall of this and many models is controlling the sensitivity of the model especially in a situation where heterogeneity of soil contamination amplifies the variability of the model, although it is suggested that soil solution concentration should be treated as a stochastic parameter, in a similar manner to BAF. In aquatic toxicology, similar relationship can be explored by using quantitative structure–activity relationships (QSAR) in rule-based expert systems.

See also: Ecological Risk Assessment; Spatial Models and Geographic Information Systems.

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