Spatial scales in the assessment of risks of contaminants to higher organisms, with comparison to human health procedures *by N.van den Brink, U.Schlink*

Introduction

Recently, the research on the assessment of risks of contaminants in the environment for higher organisms has also been focussed on spatial aspects (see for instance Cairns et al., (1996). This included spatial heterogeneity of the occurrence of contaminants, but also the spatial variability in the occurrence of organisms. Very little literature however, is available on the explicit effects of scaling on the results of spatially explicit assessment of risks. Woodbury (2003) and Hope (2000) addressed this, and conclude that the choice of scales may affect the outcome of risk assessments. Gehlke and Biehl (1934) discussed this problem, and demonstrated that it is possible to estimate different results by applying different scales of an area of interest.
In their habitats organisms may roam at different scales, ranging from meters for worms, to km for the badgers. In the current abstract the scales in environmental studies will be addressed, including the modifiable area unit problem (MAUP). This is related to the fact that there are no absolute levels of hierarchical organisation in natural systems, except as defined by perception. The definition of scales in spatial research is therefore subject to some degree of arbitrary. However, it has been established that the choice of scale may affect the results of the research. This may then result in the fact that the outcome of a risk assessment based on spatially explicit models, may be depending on the choice of scales. This will be illustrated later with a few simple examples. Before addressing the examples, some methods to upscale or downscale data will be presented.

Methods for upscaling and downscaling

Upscaling or aggregation of environmental data can be done in several ways and techniques each with its own advantages and disadvantages (table 1). For instance, interpolation methods like kriging or related techniques leave more choice in the shape and size of support units, but require specific assumptions concerning spatial correlation and stationarity of data. Thus, a trustworthy model on spatial correlation required for kriging can only be derived from numerous observations at different separating distances. Other techniques like inverse distance weighing are more simple, and require less detailed and specific information in the data, but these techniques also give less insight in the spatial characteristics of the interpolated results, like for instance local variance. The choice of technique depends therefore on the type and quality of data, and additional information that is available.
No standard routines are available for downscaling of data. If the support is coarse, small scale variability can not be distinguished, because this variability is hidden within the coarser support units Downscaling of information can only be performed with additional information on the within-support unit variability of the characteristic that needs to be scaled down

Spatially explicit risk assessment

The first question that needs to be addressed is why a spatially explicit risk assessment (SERA) should be applied and why not a conventional approach (environmental risk assessment: ERA)? In table 2 some characteristics are given for SERA and ERA which may be used to answer this question for specific applications Generally, a SERA is more realistic and not based on for instance a worst case situation, and a SERA allows for additional solutions in space. SERA can also include spatial heterogeneity of soil characteristics and habitat occurrence, including spatially explicit feeding ecology of prey items and predators. Finally, the application of a spatially explicit risk assessment results in differentiation of risks within the area of concern, e.g. it illustrates where risks are relatively low, and where relatively high. This information may be used to allocate preferable habitat in places where risks are low, and non-preferable habitat at locations with highest risks.

Technique	Data requirements	Input	Support size and -shape	Variability within support	Quantified accuracy
Thiessen Polygons	Some observations	Observations	Defined by configuration of observations	Considered homogeneous	No, or expert opinion
Spatial aggregation	Sufficient random observations within each map units	Observations and map units	Shape and size of the map units	Estimates for map units	Quantitative per unit
Inverse distance interpolation	Assumptions on similarity with distance	Observations	Same support as observations	Considered homogeneous	No, or expert opinion
Kriging	Assumptions on spatial correlation and stationarity	Observations	Larger or equal to the observations, choice of shape is free	Considered homogeneous	Quantitative for support

Table 1. Different techniques for upscaling of data with some characteristics on data requirements and assumptions

However, it should also be noted that there are also drawbacks of a SERA. Generally a spatially explicit assessment demands for more specific data than a conventional non-explicit method. More observations may be needed, although even in non explicit assessment replication of observations is needed. This may result in higher costs of a spatially explicit assessment in comparison to a conventional non-explicit one.

	SERA	ERA	Remarks
Input	Spatially explicit input needed	No need for spatially explicit data	Replicates may be needed for RA
Costs	Costs may be higher	May be lower	Replicates also needed for RA, hence differences in costs may be less than expected
Realism	More realistic,	Less realistic	In a SERA spatial heterogeneity of contaminants and habitat can be incorporated, but also ecological characteristics of the species of concern
Possible solutions	Habitat reconfiguration	No differentiation within area of concern	

Table 2. Some characteristics of SERA and ERA.

Examples of effects of scales on the results of spatially explicit assessment of risks

As mentioned earlier, the choice of scales may affect the results of a SERA of contaminants to wildlife. However, the advantages of the application of a SERA may be as such that further investigations of the effects of scales may e worthwhile in order to get more insight in these possible effects of scales in order to counteract the possible drawbacks of SERA. In the next paragraphs some simple examples will be presented, which can be used to discuss such effects.

Example 1: a case with random soil contamination, random movement of the organisms and, different home range sizes

In this examples we assume the following : (1) a region represented by grid cells, with a soil contamination that results in a certain daily intake by the organisms (5 µg/day ± 1.5 (s.d.)). (2) territories are ofdifferent size: 1 grid cell, 2 cells, 4 cells, and 16 grid cells.

For each territory the average daily uptake was calculated and averaged over all territories. A total of 1024 cells were used, so in case of territories of 1 grid cell this resulted in 1024 territories, in case of 16 grid cells per territories only 64 territories could be placed within the area. In figure 2 the average daily uptake is plotted for the different home range sizes, in combination with its standard deviation, 95% percentile and the maximum observation. It is illustrated that in case the home range is just one grid cell, the distribution of daily uptake was similar to the soil characteristics, as expected (i.e. mean is 5, standard deviation 1.5). When the home range size increased the mean daily uptake did not change, however the standard deviation and 95% percentile of the observations decreased. The standard deviation decreased with the square root of the ratio between the number of grid cells between the home range sizes. Hence, when increasing the home range from one to two grid cells the standard deviation decreased on average by a factor 1.41 (square root of 2).

Example 2: a case with non-random soil contamination, random movement of the organisms and, different home range sizes

In this example the characteristics of the organisms are similar to examples 1 (random movement, and sizes of territories), but the soil contamination occured non-random or clustered, which can be illustrated by the autocorrelation of the data (figure 2). The higher the autocorrelation the more clustered the data are, hence in this figure there is a situation with high clustering, low clustering and non clustering (random). We applied this on two levels of contamination: 5ug/g (50% of the cells), and 20ug/g (also 50%). The average contamination level is then 12.5 ug/g.

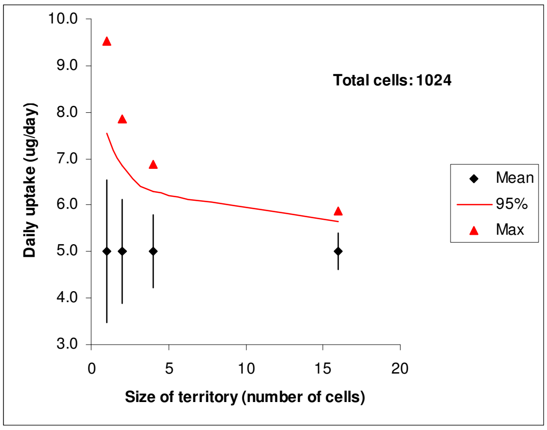

Figure 1. Results of example 1 (random soil contamination, random movement organisms, different sizes of territories), indicating that increase in home rang sizes (territory) results in a decrease in the variability of the uptake rates.

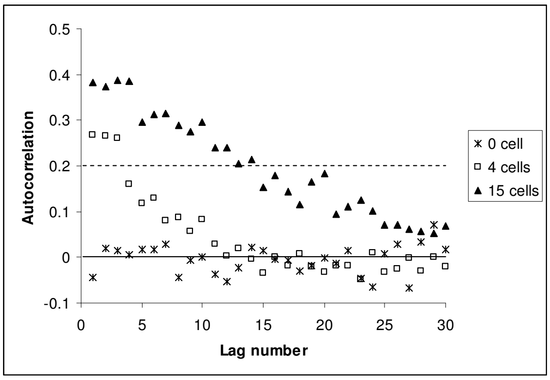

Figure 2. Three different soils: random (crosses), slightly clustered (squares) and highly clustered (triangles).

In figure 3 it is illustrated that increasing the autocorrelation did not affect the average concentrations at all, and this was also independently for the size of home range. The increasing home ranges (from Figure 3A to 3D) resulteed in decreasing standard deviations as could be expected based upon the results discussed earlier. However, this effect was different for soils with different aggregated soil concentrations. Generally, when the concentrations were more autocorrelated (15 cells) the effect of increasing home ranges on the standard deviation of the average uptake was smaller.

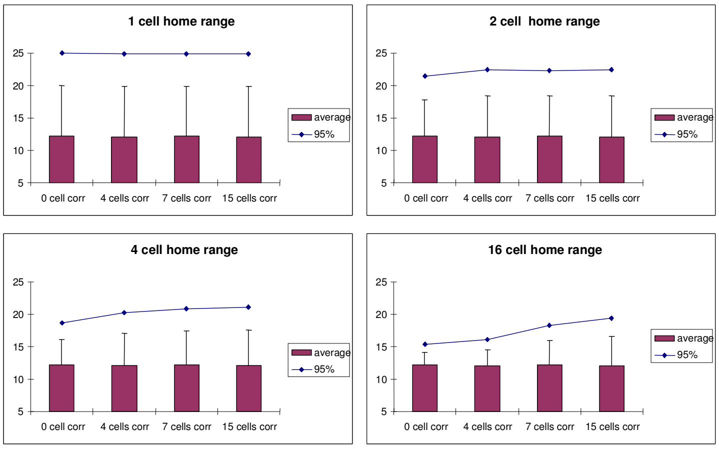

Figure 3. The effect of increasing home ranges (from 3A to 3D) on the standard deviation and 95th confidence interval of the average daily uptake by soil types with different degrees of autocorrelation (see figure 2).

Example 3: a case with random soil contamination, non-random movement of the organisms and, different home range sizes

In this example the distribution of the contaminants is random like in example 1, but the foraging pattern of the organisms was non-random. This may be due to the fact that the spatial distribution of prey items may not be random in space but for instance also be related to soil characteristics. Then, the predator may feed selectively within its home range. In this example a fictive situation is assumed in which a predator that lives in a home range of 16 grid cells only feeds in 4 of those grid cells.

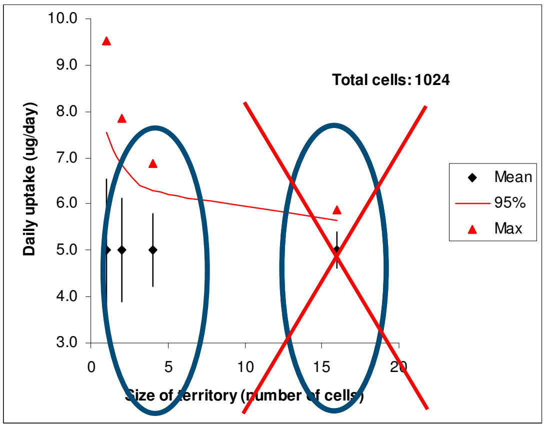

Figure 4. Effect of selective feeding in 4 cells in a home range of 16 cells on the statistics of the average daily uptake.

Based upon the size of the home range one would expect the statistics related to 16 cells size, however due to the fact that only 4 cells were effectively used, it can be deduced that the statistics of the average uptake were not related to the size of the home range, e.g. 16 cells, but to the size of the feeding range, e.g. 4 cells (figure 4). This resulted in a more variable uptake than expected on home range size. This example illustrates that not just the home range of an organisms is of importance for scaling issues, but even more so the functional use of the home range.

Effects of scaling issues in environmental issues: overview

The examples show that there are clear effects of the choice of scales to be expected on the uptake statistics. It should be noted that these effects are related to the ratio between the size of the grid cells and the size of the home range or feeding area. So, the results above can also be interpreted as such that the aggregation of information into larger grid cells, and the same home range or feeding range will decrease the variability of the resulting uptake figures.

In table 3 the effects of some spatially explicit factors are listed. It can be seen that size of home range, or clustering of soil contamination mainly affect the variance of the average uptake. Selective feeding, and habitat related feeding or feeding on specific food chains may result in an increase or decrease of the average uptake. This is depending on the relationships between for instance food availability in a certain area and the concentrations in that area. It is known that for instance earthworms may occur in areas with higher amounts of organic carbon in the soil, but this may also be the most polluted areas in floodplains. In such case specific feeding on earthworms may not only increase the variability of the uptake figures but also the average uptake.

Scaling factor	average exposure	variance exposure
Home range size	-	+
Clustering soil concentrations	-	+
Selective feeding in space	+	+
Habitat relationships/food chain	+	+

Table 3. effects of some spatially explicit factors on the statistics of exposure

Scaling issues in human exposure modelling

Models used in human health assessment and described by Strebel et al (2006) are different to the models that are applied in ecological risk assessment, which are generally based on simulation models. This is due to the fact that in human health assessments, data on incidence of diseases, effects or exposure are mostly available. In the ecological risk assessment only environmental concentrations and conditions can be assessed, and sometimes some indication on the levels in organisms is available. The exposure of organisms to the compounds under study needs to be calculated, using the spatially explicit exposure models of the risk assessment procedure. This difference between the data in a human health assessment and ecological risk assessment demand for different methods and models to analyse the risks, e.g. more statistical for human health and simulation models for environmental assessment. Due to these differences, issues on scales may affect the results of an assessment of human risks and ecological risks differently. Nevertheless, application of larger scales in both the human risk assessment and the ecological risk assessment generally results in the smoothing of spatial heterogeneity, and thus may result in a decrease of the variance of the results. In both disciplines specific methods and techniques are available to upscale data. For human health assessment both aggregation methods and clustering methods can be used, while for basic data in ecological risk assessment interpolation methods may play a more important role. Furthermore, in ecological risk assessment food web models are considered to be of prime importance, because exposure of organisms to soil contaminants is assumed to be mainly through food web interactions. In human health assessment other routes of exposure (inhalation, occupational), each with its specific scales, may also play an important role.

Rules of thumb in scaling issues related to SERA

Firstly there is no generic answer to the question which scale should be used in specific cases. This is case specific and related to data availability and quality, range of scales present in the case, types of answers needed etc. However, if one would like to retain as much variance and details as possible, one should aim for a small scale approach. This may be useful when not only the average uptake is demanded for but also the distribution or the 95th percentile of the uptake. Another factor for choosing the scale may be that one of the needed parameters is coarse scaled and no information is available to downscale this to a more detailed scale. When this is the case, there may be no need for more details in other parameters. Furthermore, information on movement of prey items may be limited. If so, the assumed home range or dispersion range of the prey items may be the scale to work with. In this respect different arguments can be presented, but it should be noted that: *Scales matter, and that the choice of scale may affect the results!*

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