Cost-effective risk assessment of pesticide leaching at field scales: quality versus quantity of information

D C Lambkin, M Wood, ^L ^P Simmonds

Department of Soil Science, The University of Reading, PO Box 233, Whiteknights, RG6 6DW, UK

Email: d.c.lambkin@reading.ac.uk

ABSTRACT

This paper addresses the issue of how to obtain effectively and efficiently the information needed as the input parameters for pesticide leaching models, in the context of risk assessment at the field scale. A key question is the extent to which low-cost/less-accurate information at a number of locations in the field is more useful than high-cost/more-accurate information on a few (even single) samples. An example is presented which considers the balance between quality and quantity of information for several soil properties, including soil texture, soil organic matter, adsorption and degradation, based on the spatial variation in the predicted leaching losses of isoproturon from a sandy loam soil in southern England. **2001 BCPS SYMPOSIUM PROCEEDINGS NO. 76:** Perticide Behaviour in Solis and Water
Coincillective risk assessment of perticide Heching at field scales: quality versus quantity
of information
DC Larshin, N Word, LP Simmonds

INTRODUCTION

It is not feasible to assess pesticide leaching at the field scale by integrating direct measurements of leaching from all parts of the field. Instead, conclusions are reached by studying sub-samples taken from the field, either by direct experiment (e.g. using lysimeters) or by modelling. Simulation models have becomeindispensable research tools for describing movement of water and solutes into and through the unsaturated zone (Wösten et al., 1990) and are increasingly used in pesticide registration procedures.

Geostatistics optimises the interpolation between sampling sites, providing a powerful tool for predicting values of a soil property at points where no observations have been made, or over larger areas of land (Oliver et al., 1996). As a result, fewer sampling sites are needed to achieve the same level of precision (Di et al., 1989). An obvious next step is the application of geostatistical techniques to field measurements, generating inputs to solute transport models, and carrying out distributed modelling to predict spatial patterns of leaching within the field.

Oliver *et al.* (1999) used the LEACHP model, in combination with geostatistics, to predict leaching of atrazine at the field scale. The simulation results predicted that significant losses of atrazine below ¹ m depth would have occurred from just 10% of the field and that the contribution from the rest of the field was negligible. They concluded that, when pesticide leaching is marginal, most of the pesticide leached at the field scale is likely to be contributed by vulnerable zones that comprise a relatively small proportion of the total land area.

The identification of vulnerable zones within fields requires spatially distributed sampling involving large numbers of samples, and this has severe logistical implications. For example, pesticide transport models require parameterisation of adsorption, degradation and soil

field, pedotransfer functions (PTFs) have been developed to estimate the properties from measurements of soil organic matter (SOM), bulk density (BD) and particle size distribution (PSD) (Brooks & Corey, 1964; Mualem, 1976; Van Genuchten, 1980, Hutson & Cass, 1987; Tietie & Tapkenhinrichs, 1993).

Such an approach simplifies the measurements to be made but does not decrease the amount of data required. For example, prediction of soil hydrodynamic properties in a single field using PTFs can require three measurements (PSD, SOM, BD) at three depths at each point. Geostatistics requires at least 100 data points (Oliver et al., 1996) giving a total of 900 laboratory determinations.

Therefore the laboratory measurements need to be reduced to minimise the total workload, but not at the expense of predictive accuracy. It can be argued that, where the variability of soil properties is high or a high level of precision in interpolation is desired, the number of sampling sites cannot be substantially reduced (Scheinost & Schwertmann, 1995). However, although spatial variation of a given parameter may be great, solute transport models may not be sensitive to that variation and it may be possible to reduce the number of measurements or use a single, average value for the field. When the parameter varies spatially, and the model is sensitive to that variation, the combined use of surrogate measurements at many locations and empirical relationships to transform the data may provea better alternative. Therefore design of cost-efficient sampling strategies for risk assessmentof pesticide leaching at the field scale must include consideration of model sensitivity to parameter variation. field, pedcorance fractions (FFEs) have been developed to extinct the properties from measurements of soli optimic narrely (COM) bulk develop (DD) and periods and distributions (FSD). There is approximately (FSD), Value o

Oliver et al. (1999) concluded that spatial variation in SOM content (associated with pesticide sorption and degradation) was very much more important in influencing the leaching of atrazine than was spatial variability in the soil hydrodynamic properties controlling the downward movement of pesticides via matrix flow. Similar results were reported by Soutter $\&$ Musy (1999). Therefore, it may be feasible to reduce the number of points where soil hydrodynamic properties are estimated and still be able to identify those zones within a field that are vulnerable to leaching.

Dubus et al.,(2000) tested four pesticide leaching models for sensitivity to input parameters and concluded that the most important criteria are: the adsorption parameters (Freundlich coefficient and exponent); pesticide half-life; SOM content and bulk density. This paper investigates the effect of spatial variation in these properties on the spatial variation in the predicted leaching losses of isoproturon from a sandy loam soil in southern England.

MATERIALS AND METHODS

The study site was a 9 ha arable field situated on a river terrace adjacent to the River Thames near Reading. The soil is Sonning Series, a freely-draining light sandy loam overlyingalluvial gravel. The field was surveyed in 1998 and a total of 90 samples were collected from the top 0-15 cm using a 5-stage unbalanced nested sampling scheme as described by Oliver $\&$ Webster (1986). Pesticide leaching losses from the top 30 cm were predicted using the pesticide leaching model SWAP (version 2.0.7d, January 2000). The input data were either measured (PSD, DT₅₀, Kd) or calculated using PTFs (SOM, BD).

Particle size distribution was determined on the ² mm fraction by laser granulometry. Pesticide degradation rate (DT_{50}) was estimated by incubation with isoproturon (IPU) for 7 and 28 days. Duplicate samples of fresh soil (equivalent to 30 g oven dry soil) were weighed into glass jars. A suspension of commercial formulation of IPU (Alpha isoproturon 500, 46.4% a.i.) in water was added to produce a dose concentration of 13.2 mg/kg. The soil was incubated at 20°C and the moisture content was maintained at 50% maximum water holding capacity. The samples were extracted with 90 ml acetonitrile:water (70:30 mix), a small aliquot was passed through ^a 0.2 um membranefilter and analysed by hple (Zorbex ODS; 5 um column; flowrate 0.8 ml/min; detection by u.v. at 240 nm). Particle aixe distribution was determined on the 2 mm fraction by laser grandeneity.

President despaisation met (71%) was estimated by incidenties of the showness (19) effects and the subsequent of constantation of the C

Loss on ignition (LOI) was determined by ignition of oven dried soil at 450°C for ²⁴ h. SOM was estimated from LOI using a field-specific PTF following the procedure described by Frogbrook & Oliver (2001). Geostatistical techniques were used to produce ^a map of LOI. Nine samples (three each from the high, medium and low LOI areas) were identified for determination of soil organic carbon (SOC) using the modified Walkley-Black procedure (MAFF,1986). The nine LOI and SOC determinations were used to produce ^a PTF for SOM.

Kd was determined for all samples by equilibrium with $0.02M$ CaCl₂ containing 5 mg/l IPU (5) g soil:20 ml solution), assuming linear adsorption. The Freundlich exponent was kept constant at 1.0 because adsorption experiments on four samples showed that adsorption waslinear in the range of concentrations modelled. Bulk density was calculated using a PTF for ploughed topsoils (Chen, 1998):

 $BD = 1.483 - 0.447C + 0.141S - 3.97SOM$

where $C =$ mass fraction of clay $S =$ mass fraction of sand $SOM =$ mass fraction of soil organic matter

Water release characteristics were calculated using a PTF within the model using the analytical function option (Mualem-van Genuchten equation) and PSD, SOM and BD.

Weather data (12 months) were selected from long-term measurements at the Reading University weather station (Sonning, Berkshire, UK). Potential evapotranspiration was calculated outside the model using the Penman-Monteith formula. The weather data were repeated to give a simulation run of three years, providing 2 years to allow the soil water status to stabilise. A crop (SWAP standard maize data) was used (sown 1 May, harvest 15 October each year). Pesticide was applied at the rate of 2.5 kg ai/ha on 15 March of the third simulation year.

RESULTS AND DISCUSSION

The model was run six times for each of the 90 field locations. The first run was the base scenario where all spatially variable input parameters (Table 1) were as measured or calculated. For each of the subsequent runs one of the parameters was held constant at the field average value.

The model accounted for between 99.92 and 100% of the pesticide applied (Table 2). At the end of the three year simulation all the pesticide had gone from the top 30 cm of the profile, except for three of the 90 locations which had slow degradation rates ($DT₅₀$ more than 30 days). The model accounted for between 99.92 and 100% of the pesticide applied (Table 2 end of the three year simulation all the pesticide had gone from the top 30 cm of the except for three of the 90 locations which had slow de The model accounted for between 99.92 and 100% of the pesticide applied (Table 2 end of the three year simulation all the pesticide had gone from the top 30 cm of the except for three of the 90 locations which had slow de

Table 1. Spatial variability in the input data for the pesticide leaching model, SWAP

Table2. Spatial variability in leaching of IPU (g/ha) at ³⁰ cm predicted using SWAP for six scenarios, with all parameters varying (base scenario) or substitution of the mean value for one parameter

In the base scenario the average amount leached at 30 cm was 47 g/ha, representing 1.9% of pesticide applied. Analysis of the variation in leaching between the locations shows that 50% of leaching was accounted for by 72 out of 90 locations and 50% by 18 locations. This confirms the bias in leaching toward a small number of locations within the field (Figure 1).

Substituting the field mean value for PSD, BD or SOM had little effect on the mean or range of amount leached. All three scenarios accounted for between 98.3% and 99.4% of the aggregated leaching of the 90 locations. The mean $DT₅₀$ and Kd scenarios accounted for 91.7% and 92.8% of the aggregated leaching respectively. This indicates that the total predicted leaching from the field could probably be estimated from field average values of these parameters, on condition that the measured value is a true estimate of the field mean. The number of samples (n) required to estimate the field mean depends on the within-field variation (standard deviation, σ), the model sensitivity to parameter (tolerance required, L) and the confidence level required for the result (Student's-t, Z): La the base sexuatio the average motont; behold at 30 can won 4 2 phn, representing 19% of
penticlea applied. Analysis of the variation in leading between the locations shows that 39%
of showing was a sounding to lead and

$$
n = (Z \ast \sigma)^2 / L^2
$$

The model is very sensitive to variation in $DT₅₀$ and Kd, and these parameters also had the greatest within-field variation. Therefore, for accurate estimation of the average field leaching, it would be more effective to take many (23) measurements of $DT₅₀$ and Kd within the field compared with few (2) measurements of particle size distribution.

Prediction of leaching vulnerable zones within the field shows similar sensitivity to DT₅₀. There was no significant difference $(R > 0.98)$ between the first four scenarios in Table 2 as indicated by the small differences in range, mean, standard deviation and skew. By using the mean DT_{50} much of the variation in predicted leaching was removed, resulting in a narrower range of values.

The root mean square error (RMSE) wascalculated (Table 2) to compare the accuracy of each of the predictions compared with the base scenario. Comparison of RMSE showsthat the accuracy depends on $Kd > DT₅₀ >> BD > PSD > SOM$ and that the RMSE for DT₅₀ and Kd is an order of magnitude greater than for the other parameters. These results differ somewhat from those reported by Dubus *et al.* (2000), who predicted that the relative importance of the parameters decreased in the order $Kd > DT₅₀ > SOM > BD > PSD$ for a similar compound and soil type.

CONCLUSIONS

These results indicate that spatial variation in pesticide half-life and adsorption are the most important parameters for the estimation of total pesticide leaching and spatial variation in leaching. But the results should be treated with caution: firstly, they are the results from only one model that utilises a simplified pesticide fate routine. They refer to results for only one pesticide and one field. Two parameters have been ignored that were identified as significant by Dubus *et al.*, (2000), namely the Freundlich exponent and preferential flow. Work is currently in progress to investigate how these vary at the field scale.

ACKNOWLEDGEMENTS

This work was funded by the NERC Environmental Diagnostics Programme. The authors thank Mr O R Price for the use of his data.

REFERENCES

- Brooks R H; Corey A T (1964). Hydraulic properties of porous media. Hydrology paper No.3. Colorado State University, Fort Collins, CO, 27p.
- Chen Y; Tessier S; Rouffignat ^J (1998). Soil bulk density estimation for tillage systems and soil textures. Transactions of the ASAE, 41: 1601-1610.
- Di H J; Trangmar B B; Kemp R A (1989). Use of geostatistics in designing sampling strategies for soil survey. Soil Science Society of America Journal, 53: 1163-1167.
- Dubus ^I G; Brown C D; Beulke S (2000). Sensitivity analysis for leaching models used for pesticide registration in Europe. SSLRC report for MAFF PLC532, Silsoe, Beds., UK, 85p.
- Frogbrook ^Z L; Oliver M A (2001). Comparing the spatial predictions of soil organic matter determined by two laboratory methods. Soil Use and Management. In press.
- Hutson ^J L; Cass A (1987). A retentivity function for use in soil-water simulation models. Journal of Soil Science, 38: 105-113.
- MAFF (1986). MAFF Reference Book 427: The analysis of agricultural materials, $3rd$ edn, HMSO: London.
- Mualem Y (1976). A new model for predicting the hydraulic conductivity of unsaturated porous media. Water Resources Research, 12: 513-522.
- Oliver M A; Webster R (1986). Combining nested and linear sampling for determining the scale and form of spatial variation of regionalized variables: Geographical Analysis, 18: 227-242.
- Oliver M A; Webster R; Mcgrath ^S ^P (1996). Disjunctive kriging for environmental management. Envirometrics, 7: 333-358.
- Oliver M A; Simmonds ^L P; Wood M (1999). Use of geostatistics to determine spatial variation in pesticide leaching — preliminary findings. In: Human and environmental exposure to xenobiotics. eds. A.A.M. Del Re, C. Brown, E. Capri, G. Errera, S.P. Evans & M. Trevisan. pp 551-559. Proceedings of the XI Symposium Pesticide Chemistry, Sept 1999, Cremona, Italy. ACKNOWLEDGENENTS

11. in order was functed by the NERC Environmental Diagonovics Programme. The authors

thus, ke COR risks for the use of this dia,

NEFERENCES

Rooks Re. Coreey AT (1984). Injuriant properties of proximi
	- Scheinost A C; Schwertmann U (1995). Predicting phosphate adsorption-desorption in ^a soilscape. Soil Science Society of America Journal, 59: 1575-1580.
	- Soutter M; Musy A (1999). Global sensitivity analyses of three pesticide leaching models using a Monte-Carlo approach. Journal of Environmental Quality, 28: 1290-1297.
	- Teitje O; Tapkenhinrichs M (1993). Evaluation of pedotransfer functions. Soil Science Society ofAmerica Journal, 57: 1088-1095.
	- Van Genuchten M Th (1980). A closed-form equation for predicting the hydraulic conductivity of unsaturated soils. Soil Science of America Journal, 44: 892-898.
	- Wösten J H M; Schuren C H J E; Bouma J; Stein A (1990). Functional sensitivity analysis of 4 54: 832-836.

.
2001 BCPC SYMPOSIUM PROCEEDINGS NO. 78: Pesticide Behaviour in Soils and Water 2001 BCPC SYMPOSIUM PROCEEDINGSNO.78:Pesticide Behaviourin Soils and Water

Metamodeling to assess pesticides leaching on a wide scale

L Padovani, E Capri

Istituto di Chimica Agraria ed Ambientale, Universita Cattolica del Sacro Cuore, Via Emilia Parmense, 84 - 29100 Piacenza, Italy. Email: chimiv@pc.unicatt.it

M Trevisan

DISAPROV— Universita degli studi di Perugia — Borgo XX Giugno, ⁷² - ⁰⁶¹²¹ Perugia, Italy

ABSTRACT

A simplified meta-model methodology has been applied to assess the spatial distribution of potential groundwater contamination from pesticides. The approach is based on ^a one-dimensional leaching model (LEACHP) linked to ^a geographic information system (GIS). A statistical technique to summarise the model inputoutput relationships (stepwise regression procedure) in order to upscale the estimated concentrations. The potential for atrazine leaching was estimated for the agricultural area of Piacenza province (Northern Italy).

INTRODUCTION

In the last decades an increasing number of mathematical models to predict environmental fate of pesticides have been developed, with particular attention to pesticides leaching. However, because of the amount of input data and the large numbers of simulations required to cover large areas (regional/national), these physically based techniques are generally timeconsuming and economically unfavourable. Thus, it is required a methodology to extrapolate results from local scale to a nation-wide scale taking into account at the same time the geographic variability of the model input parameters. **2001 BCFC SYMPOSLIMA PROCEEDINGS NO. 78: Perticide Behaviour in Soils and Water

1 Future 1 shows the Corpic definition of a showstabe. Future and

1 Future 1 showstabase and the model of the model of the data base of

1**

We developed an approach based on a one-dimensional leaching model (LEACHP) linked to a geographic information system (GIS) anda statistical technique to summarise the model inputoutput relationships (stepwise regression procedure) in order to upscale the estimated concentrations. The resulting frequency distributions map of the pesticide leaching concentrations can be used in sustainable groundwater management and decision making.

MATERIALS AND METHODS

Pesticide Leaching Model

The pesticide fate and transport model LEACHP (Wagenet & Hutson, 1995) was used for this study. LEACHP is ^a one-dimensional finite difference model describing the water and chemical regime in unsatured or partially saturated soil profiles. All spatially-distributed parameters required as input by the model(soil type, crop type, climate and hydrology) were external text files consisting of input data for the model. Afterwards the output files resulting external text files consisting of input data for the model. Afterwards the output files resultin
from simulations are read and processed to create leaching pesticide concentration maps. from simulations are read and processed to create leaching pesticide concentration maps. r the model. Afterwards the output if
reate leaching pesticide concentration xt files consisting of input
ations are read and process

Figure 1. Link of LEACHP model to GIS and metamodel development to create map pesticide leaching concentrations. of

Study area and scenario of application

The approach developed was applied to the plain area in Piacenza Province (Po Valley, Northern Italy) covering approximately 1,100 km'. The intensive agriculture in the area, associated with the peculiar structure of the aquifer creates a situation where the groundwater risks contamination by pollutants of agricultural origin.

The basic cartography utilised in the study was the soil mapat ^a scale of 1:50.000 defined by 23 different types of soil units: in 40% of the area the soil texture can be classified as silty clay averages of precipitation and temperature (1990-1997) was derived from daily weather data. Evapotranspiration was estimated via the Thornthwaite equation.

Atrazine was the herbicide considered in the simulations ($DT_{50} = 44$ d; $K_{oc} = 118.4$ L/kg; $K_H =$ 1.38E-06) applied once per year to a maize crop at a standard dose of 1.9 kg/ha every year).

The LEACHP model was run for 306 soil sampling points selected within each cell $(2 \times 2 \text{ km})$ of a regular grid (Figure 2). Six years of simulations were performed and as model outputs we considered, according to the FOCUS procedure (FOCUS, 2000) the 80th percentiles of annual average concentration of atrazine leached below 1 meter depth.

Figure 2. Study area location and selected soil profiles used to perform simulations with the LEACHP model.

Metamodel

Statistical techniques such as stepwise regression procedures are popular methods of searching for good subset models, particularly when the number of independent models is large. In this study the software STATISTIX Version 7.0 (Analytical Software, 2000) was used to summarise the model input-output relationships in order to upscale the concentrations estimated with LEACHP.

RESULTS AND DISCUSSION

A total of 306 values were determined representing the $80th$ percentile of the atrazine leaching concentration at ¹ meter depth in 5 years. The Wilk-Shapiro test for normality suggest a logarithmic transformation of atrazine concentration ($LogATR$) as the data were not normally distributed. Then, independent variables (clay, bulk density, hydraulic conductivity, silt, organic matter, pH, sand) were analysed statistically with a stepwise regression (Table 1). Soil type has a clear effect on the magnitude of the maximum concentration: clay content and organic matter content are the independent variables with highest correlation with the atrazine leaching concentration. **S AND DISCUSSION**
306 values were determined representing the 80^{th} percentile of the atrazition at 1 meter depth in 5 years. The Wilk-Shapiro test for normality is the mass of the mass of the straine concentration

The resulting regression model ($R^2 = 0.80$) is therefore represented by the following equation:

 $LogATR = 2.28951 - (0.08088 * [clay]) - (1.21329 * [O.M.])$

Considering the clay content and the organic matter content of the remaining 3010 soil sampling points, the LEACHP estimated values were extrapolated to the whole studyarea.

In order to create a raster overlay from the point data, a geostatistical method of interpolation (ordinary kriging) was applied by means of GS" software (Gamma Design Software, 1998). The results are displayed by the aid of GIS in a thematic map of the leaching concentration of atrazine at ¹ meter depth in the Piacenza plain (Figure 3). It is possible to identify areas of concentration (18% of the study area) of pesticide are located mainly in the Nord sector, near the Po river and in southern areas characterised by low organic matter soil contents $(< 1.5\%)$. oncentration (18% of the study area) of pesticide are located mainly in the Nord sector, nearly in the Po river and in southern areas characterised by low organic matter soil contents ($\leq 1.5\%$).

Figure 3. Atrazine leaching concentrations in the Piacenza plain estimated with the LEACHP model.

A validation of the map was carried out with analytical data of pesticide concentrations in drinking water wells. The study area includes 35 wells, which form part of a regional monitoring system. Analytical data for raw water are in good agreement with the map showing that the four wells with atrazine concentrations (average concentrations of seven years of monitoring plan) greater than 0.01 µg/l fall within areas with the largest predicted concentrations.

Results suggest that this approach canbe used successfully for evaluating the contamination potential of pesticides in large areas.

REFERENCES

Analytical Software (2000). Statistix for Windows.

ESRI Environmental Systems Research Institute, Inc. (1996). ArcView GIS, Version 3.0a.

- FOCUS (2000). FOCUS groundwater scenarios in the EU plant protection product review process. Report of the FOCUS Groundwater Scenarios Workgroup, pp. 197, EC Document Reference Sanco/321/2000.
- Gamma Design Software (1998). GS⁺ Geostatistics for the Environmental Sciences, Version 3.1 for Windows.
- Wagenet R J; Hutson, J L (1995). LEACHM Leaching Estimation and Chemistry Model. A process-based model of water and solute movements, transformations, plant uptake and chemical reactions in the unsatured zone (Version 3.0). New York State College of Agriculture and Life Sciences, Comell University, Ithaca, (N.Y.) ESRU listoicomanais, Syntam Research hardina, hac (1995), ActView GIS, Version 3.6.

TeChnocology and Secretary 3.6. POCOLOGY Complement Schemes 1985-864 (1995), and the stress of the second stress of the POCOLOGY Company

Modelling pesticide input into surface waters in Germany

B Ropke, M Bach, H G Frede University of Giessen, Department of Natural Resources Management, Heinrich-Buff-Ring 26-32, D-35392 Giessen, Germany. Email: bjoern.roepke@agrar.uni-giessen.de

ABSTRACT

A GIS decision support system (DSS) is under development for estimating the magnitude and spatial distribution of pesticide losses from non-point sources (surface runoff, tile drainage and spray drift) in Germany. The cumulative annual losses of any active ingredient (a.i.) of known half-life (DTS0), adsorption coefficient normalized for organic carbon (Koc) and dosage can be calculated for approximately 400 river basins covering the territory of Germany. Furthermore, the resulting predicted environmental concentration (PEC_{sw}) can be retrieved by relating the daily input of a.i. to the daily discharge of the respective streams. Results are visualized as grid maps with a $1x1 \text{ km}^2$ resolution. Sitespecific maps of pesticide losses and PEC frequency distributions provide a basis for regional risk assessment of pesticides. **2001 BCPC SWAPOSIUM PROCEEDINGS NO. 78: Perticlet Behaviour in Sofis and Water

Mission and The profit is depicted in part into surface were information

The profit of the control of Columeter of Northern Common Ayand Re**

INTRODUCTION

Pesticide use on agricultural land frequently leads to contamination of non-target areas such as ground water or surface water bodies. An essential condition for an a.i. to meet registration requirements is to rule out contamination of these non-target ecosystems. The "realistic worst-case"is the threshold to determine when a substance can be considered non-toxic for the surrounding ecosystems. The "realistic worst case" is usually determined by laboratory experiments and does not account for the probability of this threshold value being exceeded in its regional and temporal context. The DSS DRIPS follows a probability-based modelling
approach on a regional scale by estimating the frequency of a set limit of contamination of a given a.i. and its spatial distribution.

MATERIALS AND METHODS

The modelled non-point sources of pesticide input into surface water bodies are surface runoff, tile drainage and spray drift. DRIPS follows a modular approach, calculating the load or PEC of an a.i. separately.

Runoff

The amount of a.i. to be translocated by runoff water essentially depends on the period of time elapsed between pesticide application and actual occurrence of a runoff-producing rainfall event (Mills & Leonard, 1984). It is assumed that rainfall events of 10 mm in 24 h or larger are sufficient to trigger surface runoff. The 'mean probability of runoff-producing rainfall Gumbel-Distribution (Gumbel, 1958).

$$
Tn = exp ((h_N - u_l) / w_l)
$$
 [1]

The Gumbel-parameters u and w are provided by the German Meteorological Service (DWD) with a resolution of 8.5 x 8.5 km². Distribution function parameters of 60 min and 24 h duration are currently implemented in the DSS, the latter with separate datasets for summer and winter. According to Mills & Leonard (1984), the probability of ^a runoff-producing rainfall event T_n can also be expressed as a probability density function $f(t)$:

$$
f(t) = aT \cdot e^{(-aT \cdot t)} \qquad \qquad t \ge 0 \tag{2}
$$

with aT as the reciprocal value of Tn [cf. 1] and t as the time interval between pesticide application and first runoff-producing rainfall event. A seasonal variation factor V_t was added to equation [1] to account for the more variable frequency of rainstorm occurrences in the summer season (Auerswald, 1996).

The calculation of the 'runoff volume' Qd_i caused by a runoff-producing rainfall *Pevent* is based on the USSCS's curve-number-method (SCS, 1990). The curve numbers were modified according to Lutz (1984) in order to adapt the SCS-CN-method to Central European conditions.

$$
Qdi = (Pevent - Ia) \cdot Dc + \frac{Dc}{\alpha} \left(e^{-\alpha (Pevent - Ia)} - 1 \right)
$$
 [3]

Land use and hydrological soil group of the land parcel in question determine the drainage coefficient Dc (Anderl, 1975; Auerswald & Haider, 1996). Land use data are provided by CORINE land-cover (Statistisches Bundesamt, 1997). The hydrological soil groups were derived from a soil map (BGR, 1996) by Huber et al., (1998) conforming to the SCS-CN methodology.

$$
Ia = 0.76 \cdot \left(\frac{10}{Dc} - 10\right)
$$

The initial abstraction *Ia* comprises the processes of interception, initial infiltration rate and surface storage for the time interval passing since the beginning of a rainstorm event until surface runoff starts to occur. Current soil saturation at the time of a rainstorm event is another important factor to be accounted for to calculate the runoff volume. The proportionality coefficient α of Lutz (1984) relates the current soil saturation to seasonal variation. 7*n* = eqs (*f* No. 4*g*) W_1
The Guessich mass to sep provided by the Greenan Meteorological Service (DWD)
with neveative of the X x 3- x 3 cm. Duriculate interaction of 00 min and 2- h
duricing accuracy of 00 min and

$$
\alpha = P_1 \cdot e^{(-P_2/WZ)} \cdot e^{(-P_3/Q_B)} \tag{5}
$$

According to Lutz, the base flow Qb of a catchment is the representative factor of its hydrological condition at the beginning of a runoff event. The seasonal variation of the base flow is characterized by week numbers WZ. P1-P3 are calibration factors (Grunwald, 1997). The mean annual precipitation Pyear is provided nationwide by the DWD.

The 'pesticide concentration in runoff water' at the beginning of a rainstorm highly depends on the substance's decay as well as the retention capacity of the crop and soil it was applied on. Degradation can be expressed with a first-order decay function (Mills and Leonard, 1984):

$$
W(t) = W_{dosage} \cdot e^{(-Bw \cdot t)} \qquad \qquad t \ge 0 \tag{6}
$$

where $W(t)$ is the fraction of a pesticide's initial load W_{dosege} left after degrading during the time-interval t since application. Decay is controlled by the breakdown coefficient B_w depending on the a.i.'s half-life DT50.

By merging equations [6] and [2], a probability density function can be derived (cf. Mills and Leonard, 1984) for the fraction of the initial load $W(t)$ available on the soil surface for translocation by runoff water of a rainstorm occurring t days after substance application with the probability of $f(t)$ (eq. [2]). Within the DSS DRIPS, mean values (probability = 0.5) of a.i. losses with runoff are assumed (Leonard *et al.*, 1987)

$$
W_{0Soil} = 0.5^{\frac{Bw}{aT}} \cdot W_{dosage} \cdot (1 - BG_{i,j})
$$
\n[7]

Naturally, the full quantity of W_0 is not actually transported by runoff water. A share of it is withheld by the current plant cover of the area the pesticide was applied on. It is assumed that only the portion reaching the soil is available for translocation by runoff. $BG_{i,j}$ is an index representing the degree of soil cover of crop(j) in a specific climatic zone at a certain stage of maturity (i) (Bach et al., 2000). $W_{0.96i}$ is the runoff-available pesticide load in the surface soil layer.

Only a portion of the runoff-available pesticide load $W_{0.001}$ is expected to be found in the runoff-suspension during a rainstorm event. That is the fraction of the a.i. subject to desorption processes within the first centimeters of the topsoil. Consequently, the model only calculates pesticide displacement for the liquid phase. Erosion is not taken into account. A semi-empirical approach was adopted from GLEAMS (Leonard et al., 1987) where the soluble amount of the runoff-available pesticide load can be derived by multiplying W_{0Soil} with a desorption-coefficient D_s . An instant balance of an a.i. between the liquid and solid phase is pre-supposed. D_s can be derived empirically from the distribution coefficient Kd, which in turn can be obtained from the linear organic carbon partition coefficient and the content of organic carbon Corg (CREAMS/GLEAMS: Leonard et al., 1987). where πr_{ij} is the fraction of a penticle's minial local R'_{target} , let after depending during to
these intervals in the al., but in Germany (Bach effects). By received in the al., but in Germany (Fig. 200). Hence, pe

Finally, the pesticide concentration of an a.i. in solution $Csolv_{w,t}$ can be calculated from the runoff-available pesticide load W_{0Soli} , the desportion-coefficient D_s and the distribution coefficient Kd . Csolv_{w,t} being the quantity of the initial dosage of an a.i. which has to be expected as surface water inp coefficient Kd. $Csolv_{w,t}$ being the quantity of the initial dosage of an a.i. which has to be expected as surface water input as a result of a runoff-producing rainstorm event.

$$
C_{\textit{solvwt}} = \frac{W_{0\textit{Soul}} \cdot D_s}{1 + D_s \cdot Kd} \tag{8}
$$

2.2 Leaching

Germany's registration authorities make use of the model PELMO by Klein et al. (1997) for assessing the risk of a.i. displacement via leaching. To conform to registration standards, PELMO was adopted in DRIPS as the model of choice to estimate the quantity standards, PELMO was adopted in DRIPS as the model of choice to estimate the quantity
of pesticides transported by leaching water. PELMO is used to simulate the displacement
of an a.i. to 0.8 m depth. At that depth, the le of an a.i. to 0.8 m depth. At that depth, the leachate is expected to enter a tile drainage system - if installed on the land – or be subject to further vertical translocation. In the latter case, the pesticide ultimately reaches the ground water body, if it does not fully degrade along the way. The input of pesticides into surface waters from the ground water bodyis leaching is only calculated for drained areas. A grid cell map of Germany's drained areas is provided by Behrendt et al (1999). DRIPS estimates the site-specific input $L(leach.)_{w,i,j}$ of an a.i. dosage W applied on date (i) and crop (j) via a tile drainage system.

$$
L(leach.)_{w,ij} = W_{ij.} \cdot (1 - BG_{ij}) \cdot \delta (PELMO)_w
$$
 [9]

In the same manner as for the runoff path, it is presupposed that only that amount of an a.i. is transported in the leachate, which is not subject to foliage-interception but reaches the soil. Since PELMO does not consider interception, BG is introduced as an index of the degree of soil cover of crop (i) in a specific climatic zone at a certain stage of maturity (i) . $\delta (PELMO)_{w}$ is the fraction of the initial dose of an a.i. found in the leachate at 0.8 m depth. The solution is expected to enter a tile drain at that depth leading towards a surface water body nearby.

2.3 Spray drift

Surface water input of a sprayed a.i. is expected via direct drift, for the fraction of the substance not reaching the target area but being blown into an adjacent stream. Generally, a.i. loss by drift is significantly higher for fruit- or grapevine plantations than for field crops. This is mainly due to different spraying-techniques, like the use of boom sprayers in field crops and air blast sprayers in grapevine plantations (Ganzelmeier et al., 1995). DRIPS uses the drift tables published by Germany's Federal Biological Research Center for Agriculture and Forestry (BBA) as a basis for estimating the fraction of an a.i. displaced by spray drift. The tables are also used by registration authorities to set up spraying-distance requirements for pesticides. Different tables are available for 95th, 70th and 50th percentiles providing separate spray drift values $BBA-Tab(Dist)_{w}$ for fruit grapevine and field crops each for two phenological zones and for specific proximities of surface water and site of application.

$$
L(drift)_{\text{while}} = BBA - Tab(dist)_{\text{w}} \cdot W_{ij} \cdot A \cdot G \cdot Gd_r \cdot Gbr
$$
 [10]

where $L(Drift)_{w,i}$ is the site-specific input of a.i. W via spray drift after application at date(i) in $\text{crop}(j)$. $A|G$ is a correction factor for the cropland/pasture ratio adjacent to rivers. In DRIPS A/G is set to 0.4 for cropland and 1.0 for fruit- and grapevine plantations (Bach et al , 2000). The mean drainage density of the river network Gd_r was derived from the Hydrological Atlas of Germany (HAD) by Huber et al. (1998). It is available within DRIPS as a grid map to judge the probability of an a.i. reaching a surface water body via drift. The amount of a.i. input also depends on the width of the river Gb. Larger water bodies are susceptible to higher amounts of deposition. However, mostlarger streams have adequate buffer zones shielding a.i. input to some extent. Unshielded small ditches are frequently found in agriculturally used areas prone to receive frequent deposition. In DRIPS Gb is set to 0.5 m for 1st order streams (definition of Strahler, 1957) and 3 m for 2nd order and higher. bracking is only subshared for denied zeros. A gristical map of Greensly's drained zeros is a collable product of the dening of Greensly for the dening of the such as a river of the dening experiment. If α is a respect

2.4 PEC

The model approaches described for runoff, drainage and spraydrift estimate the expected load of pesticides input into surface water bodies for a specific region and time. DRIPS will be fitted with a further module to estimate the initial predicted environmental concentration (PEC_{sw}). The module will link the three pathways calculating the a.i.'s load with hydrological data such as rivermorphology and flow duration. The basic river network to be used is provided by Behrendt et al. (1999). The network will be classified into approximately six regions (r) of similar drainage density and rivernet-morphology. Also, all surface water bodies will be classified (g) according to their volume of discharge. Significant combinations of both classes (r) and (g) such as drainage density of $2nd$ order streams in ^a certain region will be used as model variables. An evaluation of gauging station data will produce discharge values for every class on a daily basis. The ratio of the mean daily input (E) of an a.i. via runoff, drainage and spray drift into various types of surface water bodies characterized by their daily discharge (Q) yields the predicted environmental concentration of the respective surface water body. Fraction *et al.* (1999). The network will be classified into similar drainage density and rivernet-morphology. Also, e classified (g) according to their volume of discharge. 1 classes (r) and (g) such as drainage density

 $PEC_{sw} = E/Q$ [11]

RESULTS AND DISCUSSION

The model described above will be fully integrated into a GIS-shell with an easy to use graphical interface. The DSS DRIPS is set up as a userfriendly risk assessment tool for estimating the PEC_{sw} of a.l. in surface water bodies. Results will be available with fairly high temporal (eg. daily discharges) and spatial $(1x1)$ km?) resolution. The DSS offers a time- and costeffective method to assess the probability of pesticide contamination of surface waters and the resulting initial concentration of the a.i. in surface water bodies. Relatively few parameters have to be specified by the user, such as dosage, DT50, Koc, crop and date of application. Spatially discriminated maps are produced as model results visualizing the hazard potential for the territory of Germany with its varying soil field campaigns for specific ieosin Fheutpt substances at sites where high $g_{\text{very high}}$ very high \Box no application contamination is expected.

Figure 1. Map of results from DRIPS

ACKNOWLEDGEMENTS

This project is funded by the Federal Environmental Agency (UBA), Berlin: UBA-FE-Project 299 24 272

REFERENCES

- Ander! B (1975). Vorhersage von Hochwasserganglinien aus radargemessenem Regen. Mitt. Inst. fiir Wasserbau 7, Karlsruhe.
- Auerswald K (1996). Jahresgang der Eintrittswahrscheinlichkeit erosiver Starkregen in Siiddeutschland. Z. Kulturtechnik und Landentwicklung 37: 81-84.
- Auerswald K; Haider ^J (1996). Runoff Curve Numbers for Small Grain under German Cropping Conditions. J. Environ. Management 47: 223-228.
- Bach M; Huber A; Frede H G; Mohaupt V; Zullei-Seibert N (2000). Schätzung der Einträge von Pflanzenschutzmitteln aus der Landwirtschaft in die Oberflachengewdsser Deutschlands. UBA-Berichte 3/00, E.Schmidt-Verlag, Umweltbundesamt, Berlin, 274 pp.
- Behrendt H; Huber P; Kornmilch M; Opitz D; Schmoll O; Scholz G; Uebe R; Pagenkopf W; Bach M (1999) Nahrstoffbilanzierung der Flussgebiete Deutschlands. , UBA-Texte 99/75, Umweltbundesamt, Berlin.
- BGR(1996) Bodeniibersichtskarte 1:1 Mio. (BUK1000) der Bundesrepublik Deutschland. Bundesanstalt f. Geowissenschaften und Rohstoffe, Hannover.
- Ganzelmeier H., Rautmann D., Spangenberg R., Streloke M., Herrmann M., Wenzelburger H. J., Walter H F (1995). Studies on the Spray Drift of Plant Protection Products-Results of ^a Test Programme Carried Out Throughout the Federal Republic of Germany. Mitteilungen aus der Biologischen Bundesanstalt für Land- und Forstwirtschaft 305, Berlin, 111pp. A CONVINCENDATY New York New Yor
	- Grunwald § (1997). GIS-gestiitzte Modellierung des Landschaftswasser- und Stoffhaushalts mit dem Modell AGNPSm. Boden u. Landschaft Bd. 14: Giessen, 170pp. (PhD thesis, Univ. Giessen).
	- GumbelE ^J (1958). Statistics of the Extremes. Columbia Univ. Press, New York, 375pp.
	- Huber A; Bach M; Frede H G (1998). Modeling pesticide losses with surface runoff in Germany. The Science of the Total Environment 23: 177-191
	- Klein M; Miiller M; Dust M; Gorlitz G; Gottesbiiren B; Hassink J; Kloskowski R; Kubiak R: Resseler H; Schafer H; Stein B; Vereecken H.(1997). Validation of the Pesticide Leaching Model PELMO Using Lysimeter Studies Performed for Registration. Chemosphere 35 (11): 2563-2587
	- Leonard ^R A; Knisel W G; Still ^D ^A (1987). GLEAMS: Groundwater Loading Effects of Agricultural Management Systems. Trans. ASAE ³⁰ (5): 1403-1418
	- Lutz W (1984). Berechnung von Hochwasserabfliissen unter Anwendung von Gebietskenngrößen. Mitt. Inst. f. Hydrol. und Wasserwirt. 24, Karlsruhe, 221pp.
	- Mills W C; Leonard R A (1984). Pesticide Pollution Probabilities. Trans. ASAE 27: 1704- 1710
	- SCS (1990). Estimating Runoff for Conservation Practices. Texas Eng. Techn. Note No. 210-18-TX5. Soil Conservation Service. U.S. Dept. of Agriculture, Washington D.C., 47p
	- Statistisches Bundesamt (ed.) (1997). CORINE-Land-Cover, Digitale Bodenbedeckungsdaten der Bundesrepublik Deutschland. Statistisches Bundesamt,
	- Wiesbaden
Strahler A N (1957). Quantitative Analysis of Watershed Geomorphology. Trans. Am.