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Influence of input uncertainty on prediction of within-field pesticide leaching risks

Anna M.L. Lindahl [a,*], Mats Söderström [b], Nicholas Jarvis [a]

[a] Department of Soil and Environment, Swedish University of Agricultural Sciences, P.O. Box 7014, 750 07 Uppsala, Sweden
[b] Department of Soil and Environment, Swedish University of Agricultural Sciences, P.O. Box 234, 532 23 Skara, Sweden

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ABSTRACT

Previous research has suggested that pesticide losses at the field scale can be dominated by a small proportion of the field area. The objective of this study was to investigate whether site-specific applications (i.e. avoiding high-risk areas) at the field scale can contribute to a reduction of pesticide leaching despite uncertainty in the underlying model-based leaching risk map. Using a meta-model of the dual-permeability model MACRO, the annual average pesticide leaching concentrations were estimated for 162 sample sites on a 47 ha field. The procedure was repeated for different scenarios describing different patterns of spatial variation of degradation half-lives and the partition coefficient to soil organic carbon. To account for interpolation uncertainty, maps of predicted pesticide leaching risk were produced by the method of sequential Gaussian simulation. The results of the case study show that larger reductions of predicted leaching were achieved by site-specific application than by that of a comparable uniform dose reduction. Hence, site-specific-applications may be a feasible method to reduce pesticide leaching at the field-scale providing that the model approach gives reasonable estimates of the spatial pattern of pesticide leaching.

1. Introduction

European regulations impose an environmental threshold of 0.1 μg L^{-1} active substance on pesticide concentrations in groundwater (European Union, 2000). During the registration procedure, the risk of exceeding this threshold is assessed by model simulations of one or a few standard 'reasonable worst-case' scenarios that do not reflect spatial variability under field conditions. These simulations provide an overall broad-brush control on 'acceptable' pesticide losses to groundwater on a national or international scale. However, farmers who use pesticides at field and farm scales have the greatest potential to reduce negative impacts in receiving water bodies. So far, this potential is largely unrealised although information campaigns on safe use and handling of pesticides have proved useful in reducing point sources (Kreuger and Nilsson, 2001). It has been proposed that diffuse pesticide leaching could be reduced if soil variability is actively managed by applying precision agriculture techniques, i.e. Geographical Information Systems (GIS) and Global Positioning Systems (GPS), both within a field and between fields on a given farm (van Alpen and Stoorvogel, 2002). The variability in field-scale pesticide leaching risk is due to heterogeneous soil properties such as texture, structure, microbial populations and activity, and organic carbon content. Previous research (e.g. Leu et al., 2004b; Lindahl et al., 2005) suggests that just a small part of the field may account for most of the leaching. If such high-risk 'hot-spots' can be identified, leaching could be practically eliminated by site-specific application technologies, without significantly affecting crop yields.

Both index methods such as the GUS index (Gustafson, 1989) and DRASTIC (Aller et al., 1987) and simulation models such as PELMO (Jene, 1998), PRZM (Carsel et al., 2003), PEARL (Tiktak et al., 2000) and MACRO (Jarvis, 1994; Larsbo and Jarvis, 2003) have been used to predict pesticide leaching risks over large areas. Index methods are easy to use because they require few input parameters. One drawback is that they

* Corresponding author. Tel.: +46 18 671167; fax: +46 18 672795.
E-mail address: Anna.Lindahl@mv.slu.se (A.M.L. Lindahl).

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often lack important process descriptions (e.g. macropore flow). Simulation models are time consuming and data demanding, which makes them impractical to use for spatial applications. Recently, Stenemo et al. (2007) developed a neural network simulation meta-model of the dual-permeability macropore flow model MACRO for pesticide exposure assessment. This meta-model only requires a few widely available input parameters. Additionally, because it is based on the MACRO model, important process descriptions, such as those of macropore flow, are considered. This makes the meta-model suitable for investigations on the spatial distribution of pesticide leaching on field, farm and catchment scales.

The efficiency of site-specific application strategies may be adversely affected by uncertainty in the leaching predictions. Pesticide characteristics (degradation rate and sorption intensity to soil particles) are usually considered as the most sensitive parameters in any pesticide leaching model (Boesten, 1991; Dubus and Brown, 2002). In practice, the pesticide characteristics are likely to be collected from existing databases and therefore assumed to be constant for all locations in the field since it would be too costly to make measurements with a high spatial resolution. In reality, the adsorption process is spatially variable at the field scale due to its dependency on soil properties such as the soil organic carbon content, clay content, clay mineralogy and pH (Coquet and Bariuso, 2002). Moreover, the spatial variation in pesticide degradation half-life (DT_{50}) can be considerable within a field (Walker and Brown, 1983; Parkin and Shelton, 1992; Walker et al., 2001). This is because the activity of soil micro-organisms is influenced by many spatially variable factors including the availability of nutrients, pH, salinity, soil temperature, oxygen content and soil moisture content (Alexander, 1999). Soil organic carbon is a particularly important variable because it is usually the dominant factor controlling sorption and therefore the availability of a pesticide for degraders. It may also be considered as a surrogate variable, which is positively correlated with microbial activity in nutrient-limited environments (Pothuluri et al., 1990). These competing effects might explain why some studies have found DT_{50} to be negatively correlated with soil organic matter content (e.g. Rodrígues-Cruz et al., 2006), whereas others have found a positive correlation with soil organic matter content (Pussemier et al., 1997) or soil organic carbon content (e.g. Charnay et al., 2005).

The objective of this study was to investigate whether site-specific applications could contribute to a reduction of pesticide leaching despite uncertainty in the underlying model-based leaching risk map. As a preliminary case study, the meta-model of MACRO developed by Stenemo et al. (2007) was used to predict leaching of a hypothetical test compound at an intensively sampled 46.9-ha field at Bjertorp in central-western Sweden. Maps of predicted pesticide leaching risk were produced by the method of sequential Gaussian simulation, and were compared for different scenarios that describe different patterns of spatial variation of DT_{50} and the partition coefficient to soil organic carbon (K_{oc}). Field-integrated average leachate pesticide concentrations were calculated from maps produced by ordinary kriging and the likely gain from precision application was estimated for each scenario.

2. Materials and methods

2.1. Model description

The model used in this study is a meta-model of MACRO (Jarvis, 1994; Larsbo and Jarvis, 2003) based on four artificial neural networks (Stenemo et al., 2007). A classification network classifies the input pattern as belonging to one of three classes of simulated leachate concentrations (<0.01 μg L^{-1}, 0.01–1 μg L^{-1} and >1 μg L^{-1}), and then the corresponding predictive network is executed. The model predicts the 80th percentile of annual average pesticide leaching concentration at 1-m depth for an annual pesticide application dose of 1 kg ha^{-1} during a 20-year simulation. Since the model assumes linear sorption and first-order degradation, the output depends linearly on the dose, and can easily be scaled for any other annual dose. The model is applicable for spring-applied pesticides in climates similar to that of southern and central Sweden. In the MACRO simulations used to train the neural network, the soil profile was divided into three horizons (0–30 cm, 30–60 cm and 60–100 cm). To account for the decrease in microbiological activity with depth, the topsoil degradation rate coefficient was multiplied by a depth-dependent degradation factor. The factor was 0.5 for the second horizon and 0.3 for the third horizon (FOCUS, 2000). Macropores were defined as pores draining at water potentials larger than −10 cm H_2O. Soil physical and hydraulic parameters were derived using a combination of pedotransfer functions, reasonable worst-case assumptions and default values (Stenemo et al., 2007). For example, subsoil organic carbon contents were set to fixed values of 0.4% in the second horizon and 0.1% in the third horizon. The coefficient controlling mass exchange between matrix and macropores was estimated by a pedotransfer function, assuming a stronger mass exchange (i.e. weaker macropore flow) for soils of coarser texture and larger organic matter content. These procedures limit the meta-model input requirements to 5 soil properties (Table 1). This small number of widely available input parameters makes the meta-model a user-friendly method for mapping pesticide leaching risk at farm or field scales. Table 1 shows the parameter ranges used to develop the meta-model. As for all statistical models, the specific conditions in the underlying simulations used to derive it should limit the use of the model. Full technical details on the development of the meta-model are given in Stenemo et al. (2007).

Table 1
Parameter space of the meta-model

Input parameter	Range
Clay content in horizon 1 and 2	0.02–0.65
Sand content in horizon 1 and 2	0.08–0.94
f_{oc} [a] in horizon 1	0.0098–0.0895
DT_{50} [b] in horizon 1 (d)	1–100
K_{oc} [c] (cm^3 g^{-1})	3–1000

[a] Organic carbon content.
[b] Pesticide degradation half-life.
[c] Partition coefficient to soil organic carbon.