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Modeling global distribution of agricultural insecticides in surface waters

Alessio Ippolito [a, b, *], Mira Kattwinkel [c, d], Jes J. Rasmussen [c, e], Ralf B. Schäfer [f], Riccardo Fornaroli [b], Matthias Liess [c, g]

[a] International Centre for Pesticides and Health Risk Prevention, L. Sacco University — Hospital, Via G.B. Grassi, 74, 20157 Milan, Italy
[b] Department of Earth and Environmental Sciences (DISAT), University of Milano — Bicocca, Piazza dellaScienza 1, 20126 Milan, Italy
[c] UFZ, Helmholtz Centre for Environmental Research, Dept. System-Ecotoxicology, Permoserstrasse 15, 04318 Leipzig, Germany
[d] Department of System Analysis, Integrated Assessment and Modelling, Eawag: Swiss Federal Institute of Aquatic Science and Technology, Überlandstrasse 133, 8600 Dübendorf, Switzerland
[e] Department of Bioscience, Aarhus University, Vejlsøvej 25, 8600 Silkeborg, Denmark
[f] Institute for Environmental Sciences, University Koblenz-Landau, Campus Landau, Fortstrasse 7, 76829 Landau, Germany
[g] RWTH Aachen University, Institute for Environmental Research (Biology V), Worringerweg 1, 52074 Aachen, Germany

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ABSTRACT

Agricultural insecticides constitute a major driver of animal biodiversity loss in freshwater ecosystems. However, the global extent of their effects and the spatial extent of exposure remain largely unknown. We applied a spatially explicit model to estimate the potential for agricultural insecticide runoff into streams. Water bodies within 40% of the global land surface were at risk of insecticide runoff. We separated the influence of natural factors and variables under human control determining insecticide runoff. In the northern hemisphere, insecticide runoff presented a latitudinal gradient mainly driven by insecticide application rate; in the southern hemisphere, a combination of daily rainfall intensity, terrain slope, agricultural intensity and insecticide application rate determined the process. The model predicted the upper limit of observed insecticide exposure measured in water bodies ($n = 82$) in five different countries reasonably well. The study provides a global map of hotspots for insecticide contamination guiding future freshwater management and conservation efforts.

1. Introduction

An estimated 4×10^6 tons of pesticides are annually applied to agricultural land at the global scale (Sánchez-Bayo, 2011) to maintain high levels of production. This amount is equivalent to an annual application of 0.27 kg of pesticide per hectare across land surface of the earth. The environmental effects caused by these substances are fundamentally different from those of other classes of chemicals, as pesticides are intentionally designed and released into the environment to control pests and weeds. Consequently, pesticides are a major threat to terrestrial (Barmaz et al., 2010; Boatman et al., 2007; Mineau and Whiteside, 2013) as well as aquatic biodiversity and ecosystem functioning (Liess & Von der Ohe, 2005; Relyea, 2005; Schäfer et al., 2012; Beketov et al., 2013), although the global extent of their effects remains largely unknown. Similarly, the relative importance of main factors driving the exposure at a global scale needs further research. Studies performed at the local and regional scale have demonstrated that agricultural practices (Brown et al., 2008; Tang et al., 2012) and landscape features (Schriever et al., 2007) determine the magnitude of exposure. Large-scale screening approaches, such as spatially explicit models based on Geographic Information Systems (GIS), allow for rapid and cost-effective exposure estimations (Schriever et al., 2007). The identification of areas of concern can trigger regional monitoring programs and, if necessary, exposure mitigation measures.

Given that insecticides are designed to control pest insect populations, they have the potential to impair stream invertebrate populations, which are largely composed of arthropods and which play a major role in aquatic ecosystem structure and functioning (Fleeger et al., 2003; Ippolito et al., 2012; Liess and Beketov, 2011;

* Corresponding author. International Centre for Pesticides and Health Risk Prevention, L. Sacco University — Hospital, Via G.B. Grassi, 74, 20157 Milan, Italy.
E-mail address: ippolito.ecotox@gmail.com (A. Ippolito).

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Liess & Von der Ohe, 2005; Schäfer et al., 2012). Such estimation of the current state of insecticide contamination in freshwater bodies is pivotal for a targeted conservation and restoration of these ecosystems in order to achieve a satisfactory ecological quality. The need for a global scale perspective is at present particularly essential because farmers in many developing countries are changing from traditional subsistence farming to market-oriented intensive-crop farming (Sataporvanit et al., 2004). Moreover, global climate change is proposed to result in a significant increase in the global insecticide application on crops, especially in industrialized countries (Boxall et al., 2009; Kattwinkel et al., 2011).

Several field studies documented that most insecticides can enter surface water bodies via surface runoff triggered by heavy rain episodes (Van der Werf, 1996; Wauchope, 1978), and, to a lower extent, by irrigation practices (Kennedy et al., 2001). In this study we used existing raster maps (FAO & IIASA, 2006; Batjes, 2006) and spatial databases (NOAA; FAO) as input data for a spatially explicit model (Kattwinkel et al., 2011; Schriever and Liess, 2007; Schriever et al., 2007; Burgert et al., 2011) estimating the surface Runoff Potential (RP) following strong rainfall events. This RP model (Eq. (1)) used to estimate insecticide input into streams, was split into two parts to separate environmental factors (e.g. daily rainfall intensity, soil characteristics, slope of the terrain etc.), from human-controlled variables (due to agricultural practices) that determine insecticide runoff. Subsequently, the predictions of the model were compared to monitored peak flow measurements of insecticide contamination in streams of four different biogeographic regions.

2. Materials and methods

2.1. Model

We used a generic indicator (RP; Runoff Potential) that distinguishes stream sites based on key characteristics of the environment around the stream to assess the potential for insecticide runoff inputs (Kattwinkel et al., 2011; Schriever and Liess, 2007; Schriever et al., 2007; Burgert et al., 2011). The RP is based on a mathematical model (Eq. (1)) that estimates the amount (gLOAD) of a generic substance that was applied in the near-stream environment and that may reach the stream in response to a single rainfall event.

$$\mathrm{gLOAD}_i = A_i \cdot D \cdot \frac{1}{1+\frac{K_{OC}\cdot OC_i}{100}} \cdot f(s_i) \cdot \frac{f(P_i, T_i)}{P_i} \cdot p_i \cdot \left(1-\frac{I}{100}\right) \qquad (1)$$

The model equation is built on nine parameters. i: grid cell index; A_i: area [ha] of the stream corridor; D: country-specific insecticide application rate [$\mathrm{g \cdot ha^{-1}}$]; K_{OC}: soil organic carbon–-water partitioning coefficient [adim]; OC_i: organic carbon content [%]; s_i: slope [%]; $f(s_i)$: influence of slope on runoff; P_i: daily rainfall intensity [mm], T_i: texture; $f(P_i, T_i)$: volume of surface runoff due to precipitation [mm]; p_i: proportion of croplands in cell i; I: average plant interception [%].

All spatial calculations were performed with ArcGis 10 (ESRI, Redlands, CA, USA). The grid cell size used in the study was 5 × 5 arc-minutes. As a result, gLOAD reflected the mean generic exposure of a stream section that would be located in a cell and had the same environmental characteristics as the grid cell. The RP of an individual grid cell was derived as the log10-transformed gLOAD and was subsequently classified into five order-of-magnitude categories (RP < -3; <-2; <-1; <0; >0).

In addition, the model was split into two submodels: the first included all environmental variables affecting the RP (daily rainfall intensity, soil characteristics, and slope); the second incorporated those variables that are under human control (insecticide application rate, crop interception, fraction of land used for growing crops). Analogous to a well-established formulation of the risk equation (Wisner et al., 2004), the first submodel was used to construct a vulnerability map, with vulnerability taken as the natural degree of susceptibility to runoff in each grid cell. The second submodel was used to derive the hazard associated with the human management of insecticides in agriculture. The vulnerability and hazard maps show completely different ranges of variation; hence, the class boundaries for these maps were set in order to obtain five equally numerous grid cell categories (i.e. quintiles).

2.1.1. Area of the stream corridor (A_i)

No real stream courses were considered in the present study. In accordance with previous studies (Schriever and Liess, 2007; Schriever et al., 2007; Burgert et al., 2011), for each grid cell we considered a generic stream segment with one bifurcation. The near-stream environment was set to an area of 45 ha, which was derived from a two-sided 100-m stream corridor that extended 1500 m upstream from the site (the bifurcation was placed midway in the upstream corridor).

2.1.2. Insecticide application rate (D)

Country-based data on the rate of insecticide application were retrieved from the FAOSTAT database (FAO). All available data for each country referring to the years 2000–2010 were considered. Issues reported in metadata (e.g. data referred to imports only or data expressed in formulated products) were evaluated case by case and unreliable data were discarded. Countries without valid data for at least two years within the aforementioned period were omitted from analysis. The arithmetic mean of the insecticide application rate was calculated for each country, unless the specific coefficient of variation was >100%. Then, if a clear trend was observed, only the latest value was considered (most representative of the present situation), or else the country data was omitted. For those 84 out of 165 countries without respective data, the insecticide application rate was estimated. The estimation was done using a linear model with the predictors being the average accumulated temperature (see below), the fraction of insecticide high-consuming crops, and the GDP. The average accumulated temperature was included as predictor since a strong correlation between temperature and the rate of insecticide application has been identified in another study (Kattwinkel et al., 2011) for European countries.

We calculated the average accumulated temperature for each country using a map produced by FAO & IIASA (2000) ($T_{\mathrm{mean}} > 0\,^{\circ}\mathrm{C}$), then weighting the value of each grid cell in the country by the corresponding proportion p_i of croplands (taken from FAO & IIASA, 2006) to account for potential differences in temperature between crop and non-crop areas. The insecticide application rates may vary strongly among crops. Therefore, crops were divided into two classes on the basis of their typical insecticide amount requirements using the U.S. National Pesticide Use Database (Gianessi and Reigner, 2006). Insecticide high-consuming crops included all kinds of fruits, nuts and olives; insecticide low-consuming crops included all remaining crops (mostly cereals, vegetables, herbs and fiber crops). Typical insecticide application rates differed significantly between the two groups ($p < 0.0001$, Mann–Whitney and Kolmogorov–Smirnov tests). The fraction of insecticide high-consuming crops in each country was estimated on the basis of the information retrieved from FAOSTAT database (FAO) for the years 2000–2010. Finally, the insecticide application rate is also determined by the economic situation in a country. Lack of infrastructures and low capital availability may limit farmers' access to plant protection products. Therefore, we also included the country-specific GDP. GDP values (expressed in 2005 US dollars)